FINAL REPORT (ELEC-419)
AUTO-FEAT: Automatic Diabetic Retinopathy Detection

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Abstract:

Diabetic Retinopathy (DR) is a complication of diabetes that is caused by changes in the blood vessel of the retina and it is one of the leading causes of blindness in the developed world. Currently, detecting DR symptoms is manual and time-consuming process, which requires trained technicians, clinician or physicians to examine, and it generally takes up to few minutes to hours before the trained personnel provides his or her review. The purpose of this project is to design an automated and efficient solution that could detect the symptoms of DR from a retinal image within seconds and simplify the process of reviewing and examination of images.

INTRODUCTION

According to the Vision 2020 report, there were 45 million cases of blindness by 1996, out of which 15% of those were due to diabetic retinopathy or glaucoma[1]. Diabetic retinopathy is a condition that can cause damage to the blood vessels inside the eye thus leading to blindness. It is a critical eye disease, which can be regarded as manifestation of diabetes on the retina[2]. Early diagnosis, timely treatment and proper method of screening of this disease have been shown to prevent visual loss and blindness in patients with diabetes[3]. DR is classified into two types: Non-proliferative diabetic retinopathy (NDPR) and Proliferative diabetic retinopathy (PDR). NDPR is the early stage of the disease and broken down into three stages i.e. mild, moderate or severe with different signs of symptoms in each stage and the disease is still treatable at this point. PDR is the advance stage of the disease and the patient is at high risk of vision loss at this point.

PROBLEM STATEMENT

The basic fundamental problem faced with the current method of detection is that the process is completely manual and time consuming. It requires a trained doctor, clinician and/or technician to take the image and examine it for any symptoms. This process of review and examination takes up to few minutes to hours depending upon the severity and condition of the disease, and number of images or patients seen at one time[3]. Diagnosing the absence of retinopathy or presence of a single or few lesions is often more time consuming than diagnosing mild levels of retinopathy[4]. Nonetheless, the current process at many clinics requires a clinician or technician to be trained so that they can perform the initial diagnosis by examining the retinal image and provide their assessment to the ophthalmologist. While this approach is effective, its resource demands are high and costly[5]. As the number of individuals with diabetes continues to grow, the current tools to prevent blindness due to diabetic retinopathy will become even more inefficient and therefore an effective and efficient solution is needed.

MARKET SURVEY AND SOLUTION

In order to prepare for the future and drive towards efficacy and efficiency, we propose a solution that can automatically detect diabetic retinopathy on the spot. This will help in reducing the office workload and provide same efficacy, if not better, as the manual process. Improving efficiency and efficacy being our primary goal, we discovered another problem with the current examination method during our market survey. Current software's do not offer a simple feature of marking/labeling or commenting images for ease of review.

Prior to proposing the final product solution, the team completed a market survey with a few hypothesis (listed below) that could potentially help in improving efficiency and provide the same efficacy as the current manual process.

A) The automatic detection of certain eye diseases or progression of disease reduces the workload.
B) The larger FOV image will make the diagnosis of eye diseases easier for physicians.
C) Physicians would like to review images from anywhere at anytime
D) There is a class of patients that needs more frequent monitoring of images than current practice. If there was a monitoring tool that allowed home or remote monitoring, then it will have a market.

Ten (10) physicians (Ophthalmologist) were interviewed and questions were asked around the four formulated hypothesis. It was learned during the customer survey that hypothesis "A" would be good solution and assist the office by great means. Almost every physician interviewed showed interest in this solution and believed that it would serve their needs and help in reduce the workload. Although the customer survey sample size was low, other resources such as research papers (cited in problem statement), competitions (www.Kaggle.com), competitors (IRIS) trying to solve the same problem with the same solution showed that there is a great need for this feature.

While hypothesis "A" was validated through market survey, other hypotheses were also evaluated. It was realized that many products already provide a solution for hypothesis "B" and "C" and therefore this was not much of a problem right now. Similarly, "D" was invalidated as eye diseases do not progress as fast therefore patient do not need frequent visits. Nevertheless, other problems were brought up in the current technology during this interview survey. Many physicians indicated that the current software's do not provide a simple tool to mark or label images. This was of great importance to them when reviewing patient images referred to them by another physician or clinic or their own office. If a tool exist to mark and label images then they can better understand the diagnosis performed by the referrer physician or clinician. Many times, there is disagreement between two individuals and it is unclear to the referral physician as to why the initial referrer thought the patient had a certain condition. Also, if the physician or clinician can mark or label the images then when the patient is seen again during a follow up, the physician can review the clinic notes and perform re-examination faster.

INTRODUCING AUTO-FEAT

Based on market survey and current or future needs, Auto-Feat provides a software application solution that can automatically detect various types of diabetic retinopathy and provide their severity within seconds. Additionally, it shall allow physicians or clinicians to mark features and label them appropriately. The final results can be saved on the cloud so that the image can be reviewed from anywhere at anytime by any physician who has access to the server database.

For the purpose of initial prototype and minimum viable product, we designed an application that can automatically detect a particular type of diabetic retinopathy i.e. cotton wool spots (see Figure 1), which is a most common symptom associated with DR and mostly rated as severe NDPR, and is often expressed as white or yellowish fluffy circle-shaped spots[6]. The application allows the user to select an existing retinal image from the local gallery, perform instantaneous analysis on it, and returns a diagnosis on whether the eye condition is normal or abnormal. The application can then allow the user to mark and label those spots that were not detected and save the final diagnosis on local directory. Android phone-based application was chosen as it would be quick to build an application that can be tested in the field and also many futuristic retinal imaging cameras are moving towards phone based technology[7] with no robust software, thus our software can complement with their hardware and provide a complete solution. This prototype will provide a proof of concept that the application can automatically detect certain types of DR using a smartphone application.

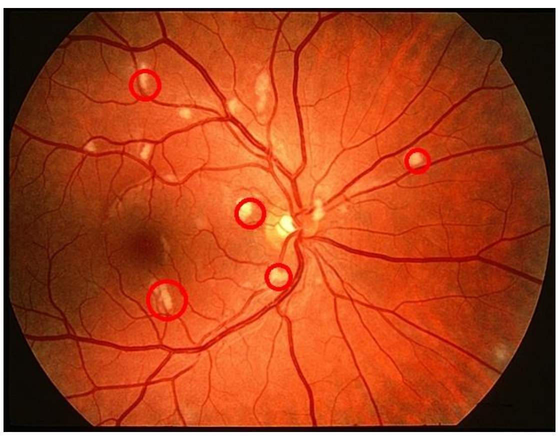

Figure 1: Cotton-Wool Spots DR

SYSTEM ARCHITECTURE

The system architecture of the prototype consists of 3 critical pieces. The Android based application platform, Amazon Web Service (AWS) for cloud computing, and feature detection algorithm build on Python that interacts with AWS for analysis. The process flow of the analysis is shown in figure 2.

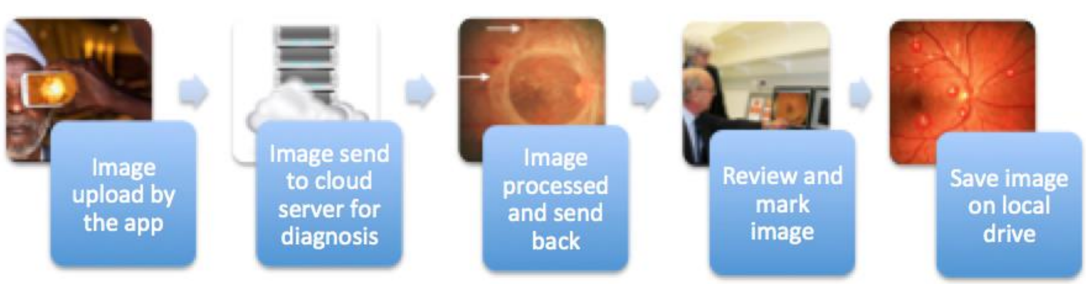

Figure 2: Image analysis process

The first step to use the application is to open the application and upload an existing retinal image (see figure 3). Once the user selects a picture, the user can select options from analyze, label or save (figure 4). If the user selects analysis, the image is sent over to the AWS server for cloud computing i.e. feature detection analysis. The server returns the analyzed image to the phone with its diagnosis results. If the image contains cotton-wool spots (CWS) then the application will display text saying "ABNORMAL" along with markings on the image showing what the algorithm detected (figure 5). If no CWS are detected, the application will display text saying "NORMAL" below the image. The user can perform additional markings or labeling on the image in case there were symptoms that were not detected by the algorithm or the user thinks there is more to the image that might need additional attention. The user can then save this image on its local directory for future review. The comments and markings on the image can be valuable for physicians as discussed previously; additionally it can serve as a feedback mechanism to the Auto-Feat group to train the algorithm with newer dataset. As the smart phones have capability to share images through email or other means, saving on the cloud for prototype was not deemed necessary.

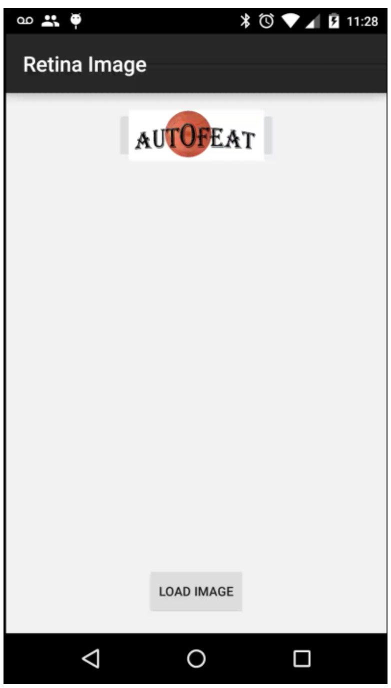

Figure 3: Image load screen

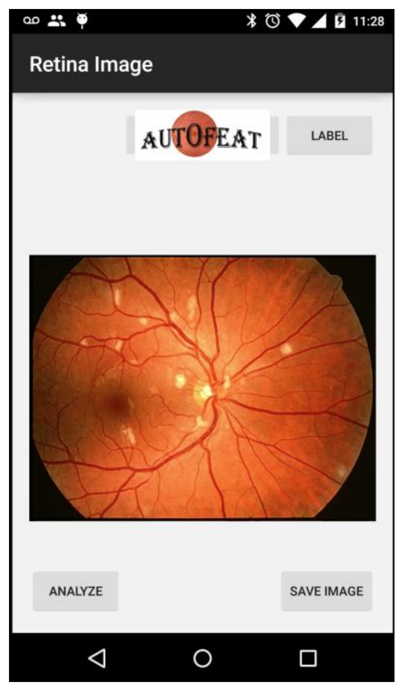

Figure 4: Loaded image

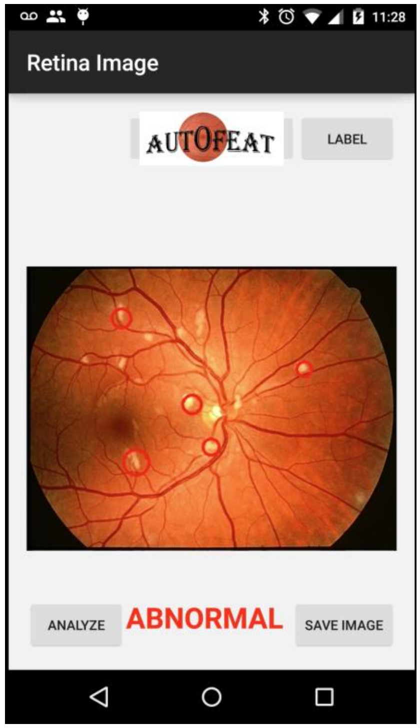

Figure 5: Analyzed image with CWS

FEATURE DETECTION ALGORITHM TECHNIQUE

In terms of algorithm, the two major methods being used here are SIFT (Scale-Invariant Feature Transform) and SVM (Support Vector Machine) and their libraries were obtained from OpenCV[8, 9]. SIFT is used to extract local feature points, and SVM is a machine learning tool. K-means clustering is used after performing SIFT to reduce the number of vector to deal with.

Given a single retinal image, the first thing we do is apply SIFT technique to obtain feature vectors of dimension 128 by 1. Depending on the complexity of the image, a large number of feature vectors might be generated. To reduce the number of vectors, K-means Cluster is applied with a K value of 1. After clustering, a single vector of size 128 by 1 is obtained, which describes all the features in the original image.

Once we know how to describe an individual image as a single vector, we increase the size of our data to include N “normal” (no DR) images and M “abnormal” (CWS) images (We use 200 images for each set, but here let’s call them N and M). First, we process every “normal” image using the technique mentioned previously, and get N vectors of dimension 128 by 1. We can put the vectors together in a matrix form to obtain a 128 by N matrix. We do the same thing to the M “abnormal” images, and get a 128 by M matrix. Both of the matrices will be fed into SVM, which generates a prediction model. Now, we have completed the training process. To test our model, we decompose a test image into a vector using the previous method, and feed the vector into the trained SVM. The SVM will generate a binary prediction on whether the machine thinks the image is “normal” or “abnormal”. This is the simple process on how the algorithm automatically predicts if the images is “normal” or “abnormal”.

CURRENT RESULTS

The initial prototype of the feature detection algorithm was trained and tested against a known dataset provided on www.kaggle.com. There are approximately 30,000 train and test retinal images that are examined and rated by trained physicians or clinicians; therefore these images can be considered as “gold-standard”. These dataset include no DR and different stages (1 to 4; with 1 being mild, 2 being moderate, 3 being severe and 4 being PDR) of DR with their identification. The algorithm was trained against 200 images with no DR and 200 images with CWS (stage 3, severe NPDR). Once trained, the algorithm was tested against 50 images with no DR and 50 images with CWS at one time. Below table shows the results from the accuracy test

		Actual Results	
		No CWS	CWS
Test outcome	No CWS	30	18
	CWS	20	32
		70%	74%

Sensitivity Specificity

The above sensitivity and specificity results are the average of 5 different sets of 50 images with no DR and with CWS. In all, the algorithm has been tested on 500 independent images. Although, the final results were not so promising; one good outcome of this accuracy test was that the algorithm was working and the method used for feature detection was implemented correctly. One obvious root cause for such low results was that the algorithm was trained with a small dataset and wide possibilities of eye colors, shape and color of CWS, shapes of blood vessel etc.

Currently, the Android application loads the image from the local directly and can allow marking and commenting on the image. It can then save the edited image on the local directory that can be reviewed later. The application is not linked to the Amazon Web-Services therefore is cannot communicate to the feature detection algorithm built on Python. Both pieces operate independently at the moment.

FUTURE PLANS

Improving the accuracy of the algorithm and enable the link between the Android application and the feature detection algorithm is the first and foremost plan for the future. The algorithm will be trained with more than thousands of images so that more types of features vectors are extracted and stored and compared against when the algorithm is tested. This will provide a fully functional one-piece prototype, which can be provided to different clinics for beta testing. We would like to receive feedback from the clinics on how we could further improve the UI and the method of automatic detection.

Next few items on the future plans, that can happen in parallel with the on-going beta testing, is to increase the scope of the algorithm to detect more types of DR and provide their severity rate, setup cloud server to store images on the server and create a computer based algorithm so that more clinics can benefit from this product.

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