Automatic Ocular Disease Screening and Monitoring Using a Hybrid Cloud System

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***Abstract*—The maturity of healthcare IoT technology which connects medical devices and applications to healthcare IT systems through internet has driven the rapid growth of healthcare. In recent years, great effort has been spent to improve ocular disease screening and diagnosis using advanced image and data analysis techniques. However, the developed systems are not widely used because they are usually offline and separated from medical devices. In this paper, we introduce a platform that connects medical devices, patients, ophthalmologists, and intelligent ocular disease analysis systems through a cloud-based system. The platform is designed in a hybrid cloud pattern to offer both easy accessibility and enhanced security. The retinal fundus images and patients' personal data can be uploaded to the public cloud tier through multiple channels including retinal fundus cameras, web portals, mobile applications and APIs. The data will be transferred to the private cloud tier where automatic analysis and assessment will be performed using advanced pattern classification algorithms. Subsequently, the analysis report will be made available in the public tier so that patients can access their own report through mobile applications or web portals. Furthermore, patients with high risk of having ocular diseases will be referred to ophthalmologists. The platform helps to form an integrated ecosystem that enables an efficient and cost-effective way of ocular disease screening and monitoring, allowing early disease detection and intervention.**

Keywords—Internet of Things, healthcare, ocular diseases, disease screening, computer aided diagnosis, cloud computing

I. INTRODUCTION

With the ageing of global population, ocular diseases affect more and more people. According to the World Health Organization (WHO), more than 285 million people globally are visually impaired due to eye diseases out of which 246 million of whom have low vision and 39 million are blind [1]. Glaucoma, age-related macular degeneration (AMD), pathological myopia and diabetic retinopathy are among the top causes of vision loss and blindness. The treatment of these diseases is extremely expensive.

Currently, ocular diseases are detected only when a person experiences symptoms such as pain or blurred vision. However, patients with irreversible diseases such as glaucoma have no symptoms until late stages. Hence, early detection and timely intervention is the only way to prevent visual impairment or blindness. Thus there is a need for a population wide screening tool that is reliable, convenient to administer and fast enough to screen a large volume of users.

Retinal fundus image has been used for years to identify risk landmarks for a variety of ophthalmologic conditions. Fig. 1 shows the appearance of the fundus images for patients with different eye conditions including glaucoma, AMD, pathological myopia and diabetic retinopathy. Over the past two decades, development in retinal image processing and pattern classification technologies has greatly influenced the diagnosis of many ocular diseases. A lot of effort has been spent to develop Computer Aided Diagnosis (CAD) systems to help ophthalmologists in both early screening and diagnosis.

Automatic glaucoma analysis from retinal fundus images has been well studied in the past few years. Most of the work aims to calculate the vertical cup-to-disc ratio (CDR), which is a widely used risk factor to assess glaucoma. Progression of glaucoma leads to more damaged optic nerves, which corresponds to higher vertical CDR values. Several methods are proposed to segment the optic disc and optic cup from fundus images, and calculate the vertical CDR based on the segmentation results [2, 3, 4]. The advantage of these methods is that they are directly extracting retinal components that are clinically relevant to glaucoma. However, the disadvantage is that the inaccuracy of different segmentations can be cascaded and hence reduces the final accuracy of calculated CDR. Other methods try to predict the CDR value using linear reconstruction based methods [5, 6]. These methods overcome the shortcomings of segmentation-based methods, and thus achieve better performance. The latest development on glaucoma screening is based on deep learning method [10]. It achieves high accuracy but takes longer to process.

AMD is characterized by central vision loss. Early AMD is usually accompanied with drusen, which is deposit of waste material near the fovea. Several methods have been proposed to detect drusen from fundus images for AMD assessment. In 11, 12], segmentation methods are used to extract drusen from fundus images. In [13, 14], a multi-level analysis approach is used to detect drusen. A further classification of different types of lesion is also performed in [14]. The most recent works focus on top-down approaches to detect images with drusen rather than drusen segmentation [15, 16].

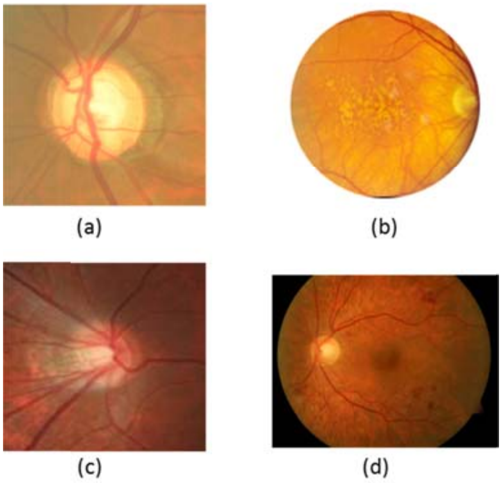

Fig. 1: Fundus images with disease of (a) Glaucoma, (b) Age-related Macular Degeneration, (c) Pathological Myopia and (d) Diabetic Retinopathy

Pathological myopia is often correlated to peripapillary atrophy, which is a pigmented crescent-shaped area caused by recession of the retina tissue. Several methods have been proposed to automatically detect peripapillary atrophy from fundus images. In [17] and [18], different methods are applied to segment the optic disc and a bigger region including optic disc and its surroundings. The difference of these two regions is identified as the peripapillary atrophy. These methods are very sensitive to segmentations and depend heavily on heuristics. A different approach is used in [19]. Instead of segmentation, biological inspired features are used in sparse transfer learning to identify images with peripapillary atrophy.

Diabetic Retinopathy (DR) can be identified by detecting associated lesions such as microaneurysm and haemorrhage. A lot of approaches have been proposed to detect lesions for DR screening [20-27]. To solve the problem of false detections on retinal blood vessels, different methods are proposed to remove blood vessels before lesion detection.

Although many automated ocular disease detection methods are well tested and validated, they are still not widely used due to the local nature of these systems. Moreover, there is a lack of data for continuous improvement of these systems.

In recent years, there have been rising interest in The Internet of Things (IoT) especially in healthcare. IoT has been identified to have potential to revolutionize healthcare in terms of improving access to care, increasing the quality of care and reducing the cost of care. With the advancement of IoT and cloud computing, there is potential to promote automatic ocular disease screening and monitoring to the general population.

In this paper, we propose a hybrid cloud based system for automatic ocular disease screening and monitoring. The system takes advantage of the rapid growing IoT technology, cloud computing and advanced pattern classification based ocular disease assessment. The rest of this paper is organized as follows. Section II introduces the overview of the concepts. Section III describes the system architecture and implementation. Section IV discusses about the whole system. Section V concludes the paper.

Fig. 2: The proposed cloud-based ocular disease screening service model

II. Overview of Concepts

This section provides insights of the current ocular disease management approach, clinical unmet needs and the proposed ocular disease management ecosystem.

A. Problem Statement

The aging population has greatly challenged the world's health systems, especially for eye health where there is a high entry barrier. In developing countries, healthcare resources are mainly concentrated in big cities. Many patients in the rural area need to travel long distance to big cities for better care. It not only increases cost, but also worsens the crowding situation in these cities. In developed countries, patients need to wait for weeks or even months to book an appointment to visit a specialist. Many of these patients do not have eye conditions but cannot be confirmed by general practitioners. Thus, it leads to the results of specialists seeing a lot of non-critical patients and critical patients waiting long time for treatments. This leads to a waste of both specialist's and patients' time, and inefficiency to the healthcare system.

Another problem is the symptom-based ocular disease detection, which is neither sensitive nor robust. For many diseases, once symptoms become obvious, it's very difficult or expensive to recover the vision.

All the problems are caused by the lack of early ocular disease screening programs. Such programs are very difficult to implement because a large number of trained professionals are needed. It usually takes years to train a grader in ophthalmology.

B. Proposed Ocular Disease Screening Model

With the advancement of medical imaging technologies, the medical imaging device becomes cheaper and cheaper Traditional fundus cameras are now available in most clinics and many optical shops in developed countries. They are also accessible in many big clinics in developing countries. The invention of handheld fundus cameras in recent years has made fundus imaging more affordable.

The popularity of smart phones and tablets has driven the internet penetration to a higher level. According to Internet Live Stats [28], about 46% of the world's population have access to the internet. Along with internet, cloud computing is also growing rapidly. Thousands of applications or services are added to the cloud platform every day, bringing cloud computing closer to people's daily life.

The advancement of image and data analytics technologies has addressed the problem of lacking trained professionals. The algorithms can learn from senior ophthalmologists in analysing the risk of having different kind of ocular diseases from images and clinical data. The predicting accuracy can be as good as or even better than trained graders given a big training dataset.

Based on the above factors, we propose an ocular disease screening service model that forms an integrated ecosystem of patients, clinics, optical shops, screening service providers and ophthalmologists. Fig.2 shows the flow of the proposed eye care ecosystem. Patients firstly go to clinics or optical shops that have fundus cameras for eye screening. Fundus photographs will be taken, which will be uploaded to cloud servers for automatic analysis of ocular diseases. A medical reported will be generated indicating risk of having different ocular diseases. Patients with high risk of certain diseases will be referred to specialist for follow-up. Cloud-based ocular disease assessment has the following features:

- A rich suite of algorithms based on pattern abstraction & recognition with improved performance
- Objective assessment of the likelihood of ocular diseases
- Ocular disease assessment report
- Ocular disease progression monitoring
- No need for specially trained professionals
- High throughput with 24 x7 availability
- Allows large scale screening
- Hybrid cloud architecture allows easy access to local and international partners.

III. System Architecture and Implementation

A. *Architecture*

Fig. 3 illustrates the architecture of the cloud-based automatic ocular disease screening and monitoring system. The system consists of data acquisition, public cloud tier to interact with various clients and systems, and private cloud tier to host patented ocular disease assessment algorithms and sensitive information. The architecture is designed to enhance both accessibility and security.

B. *Data Acquisition*

Data acquisition can be performed in multiple ways. The most common way is to extract retinal fundus images and patients' data from traditional fundus cameras which are integrated with a desktop computer for data processing and storage. Similarly, data can be acquired through handheld or portable fundus cameras. Different from traditional fundus cameras, smart phones are used for both image capturing and storage. In addition, patients' images that were taken in the past can also be used for the screening. Data acquired by all

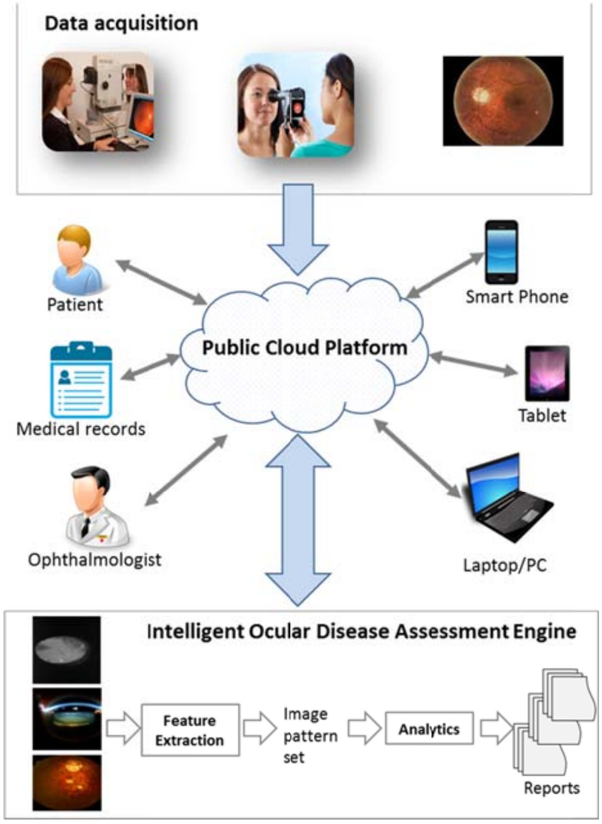

Fig. 3: Architecture of proposed cloud-based ocular disease screening and monitoring system

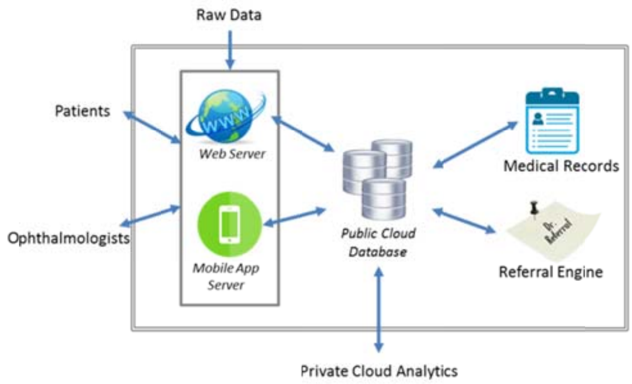

Fig. 4: Setup of public cloud tier

ways will be uploaded to the public cloud tier through HTTP REST API either by web portals or mobile applications.

C. *Public Cloud Tier*

The public cloud tier plays an important role in transmission, storage, and interaction with patients and ophthalmologists. Main components in the public cloud tier include web portals, mobile app servers, load balancer, patient record database, and doctor referral engine. Fig. 4 shows the design of the public cloud tier.

Mobile App servers and web servers are connected to a central database. The web portal was built using CakePHP, a

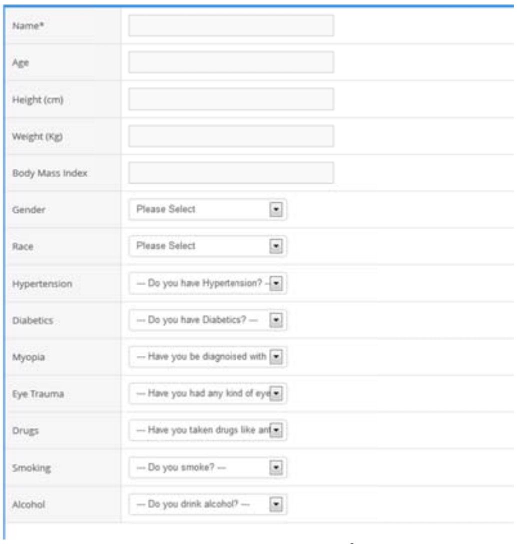

Fig. 5: Patient registration form

PHP based open-source framework that follows the model-view-controller (MVC) approach. The iOS and Android versions of the App were developed using the official development platforms of Xcode and Android Studio respectively. These portals can be used for several purposes. Firstly, patients can request ocular disease screening and analysis service on their own by uploading retinal images and personal information such as race, age, weight, gender, medication, other health conditions and life style factors. Fig. 5 shows the patient registration form with personal information. After the analysis, the result will be transferred back to the public cloud tier and a personalized analysis report for each disease will be generated. Fig. 6 shows a sample report for glaucoma risk analysis. Secondly, patients can monitor their health conditions by tracing and comparing medical reports over time. Thirdly, a referral engine is available for making appointments with ophthalmologists for patients with high risk. The system will automatically recommend ophthalmologists with their available time slots and notify patients to confirm their selections. Lastly, screening service providers can upload raw data to the system either by individual patient or by batch. The results will be returned to screening service providers' server for follow-up.

D. Intelligent Ocular Disease Assessment Engine

The intelligent ocular disease assessment engine is hosted in the private cloud tier as the algorithms require big amount of computing power and are patented. Moreover, it is usually very difficult to migrate these algorithms to the public cloud as they are developed in different platforms and environments. The intelligent ocular disease assessment engine in the private cloud contains a rich suite of algorithms that analyses the risk of glaucoma, AMD, diabetic retinopathy and pathological myopia. For glaucoma detection, a quantitative glaucoma risk measure is generated through intelligent analysis of 2D retinal fundus images [6]. The optic disc is first segmented and reconstructed using a novel sparse dissimilarity-constrained coding (SDC) approach which considers both the dissimilarity constraint and the sparsity constraint from a set of reference discs with known glaucoma risks. Subsequently, the reconstruction coefficients from the SDC are used to compute the risk measure for the testing disc. For AMD assessment, the system automatically detects the presence of drusen from macula-centered fundus images [16]. The optic disc is first detected as a reference point for the macula. Then, the macula center is localized by a seeded mode tracking approach. Subsequently, a region of interest is extracted as a square centered at the macula center with two disc diameters to each border. Features are extracted from the region of interest by dense sampling and semantic feature extraction. Finally, the presence of drusen is achieved by a classification by a support vector machine (SVM). For diabetic retinopathy analysis, the method in [27] is used to determine the presence of red lesions in fundus images. A modified version of Frangi filters is applied to sub images of the green channel to reduce effects of blood vessels. Features are then extracted from filter response maps for training of two SVM classifiers with RBF kernel, one for each type of red lesion. The classifiers are used to predict presence of red lesions. Pathological myopia assessment is performed using method proposed in [19]. A focal region is first segmented using an adaptive thresholding method. Biologically inspired features are then extracted from the focal region. Selective pair-wise discriminant analysis is used in sparse transfer learning to classify presence of peripapillary atrophy.

The four functions in the intelligent ocular disease assessment engine are configured as different sub-systems (Fig. 7). The advantage of the setup is that it enables users to choose screening service of any disease or any combination of diseases.

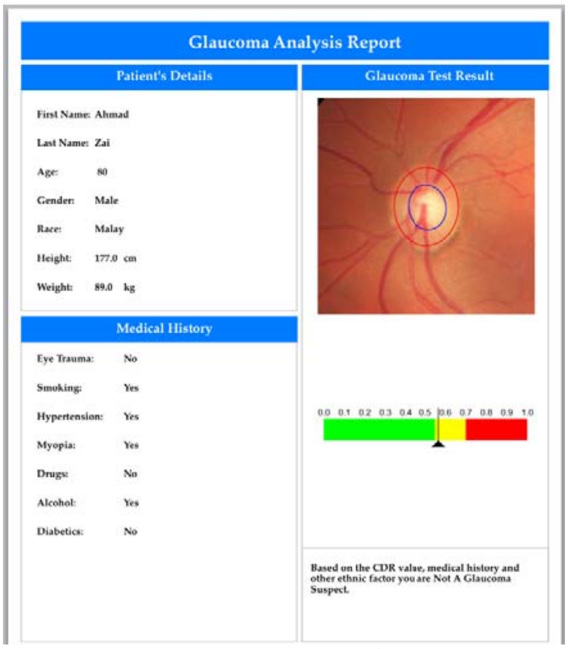

Fig. 6: Sample risk analysis report for glaucoma

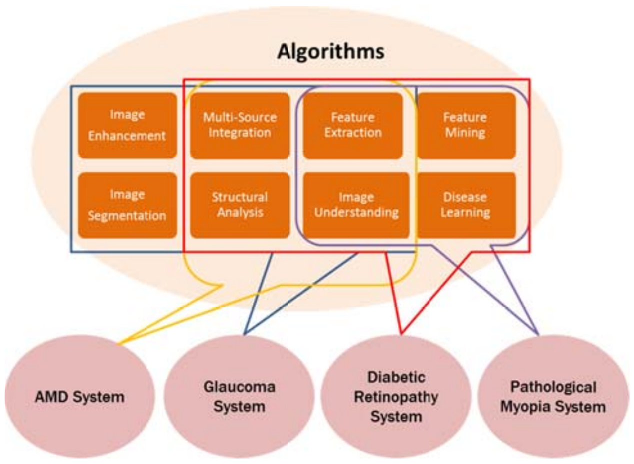

Fig. 7: Setup of the intelligent ocular disease assessment engine

IV. DISCUSSIONS

The use of a cloud-based ocular disease screening and monitoring platform brings many persuasive advantages and benefits to both patients and the healthcare system.

The automated analysis of images is fast, consistent, objective and repeatable. It usually takes 10 to 20 minutes for an experienced grader to analyze images of a patient. However, the same work can be completed within 2 minutes in the proposed system. Other problems with manual assessment include subjectivity and inconsistency. Every grader interprets clinical cases based on their own understandings which results in both inter-observer and intra-observer variations. Automated assessment has no such problems and produces objective and repeatable results, thus increasing the quality of the screening service. Moreover, a cloud-based platform allows the system to have a wider reach, enabling access anywhere through computers, tablets or mobile phones. It greatly improves access to the eye care services. Furthermore, such a cloud-based system is inherently scalable and the solution can be quickly scaled up from small-scale testing to its full use in population-based tele-screening. Finally, it enables early detection and hence early intervention of ocular disease in a cost-efficient manner.

V. CONCLUSION

In this paper, we present an online cloud-based service platform for automatic ocular disease screening through the use of medical image-based pattern classification technologies. Leveraging on the fast development of intelligent analysis algorithms for glaucoma, age-related macular degeneration, pathological myopia and diabetic retinopathy, the system can detect ocular diseases in an objective and consistent way. The saving of human resources and ubiquitous anywhere access nature of the service through the cloud platform facilitates a more efficient and cost-effective means of ocular disease screening. It allows the diseases to be detected earlier and enables early intervention for more efficient intervention and disease management.

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