Assisted OCT diagnosis embedded on Raspberry Pi 4

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***Abstract*—Machine learning in recent years has raised interest in medical imaging application, also on OCT imaging due to the straights to determine clinically significant features for diagnostics and prognostication, with potential to boost biomedical imaging interpretation and medical decision making. Evolution of hardware nowadays made possible to embedded ophthalmology imaging and machine learning techniques for a faster and precise assisted diagnosis. A downside of machine learning is the necessity of powerful hardware to compute, with latest generations of CPU or GPU to run. Low-cost effective calculation is required in this case. In this paper, successfully ported on a Raspberry Pi 4 board and reviewed machine learning algorithms to predict the presence or absence of abnormalities in the retina. A predefined dataset has been used, composed of three different diseases of the retina and a normal case of the retina. The system is portable, making it easy to be used by doctors or resident physician in their knowledge improvement.**

***Index Terms*—classification, cost effective, embedded on Raspberry Pi 4, machine learning, optical coherence tomography.**

I. Introduction

Optical coherency tomography (OCT) scans are non-invasive and high-resolution method that generates cross-sectional images at tissue level. OCT scans are mainly used, but not limited to, diagnostic and evaluation of eye conditions, from which it can be remained of eye degeneration such as macular diseases, glaucoma, diabetic retinopathy and central serous retinopathy. OCT technique has higher resolution of 20-5 μm [1] compared to similar medical procedures used for imaging such as ultrasound scanning and magnetic resonance imaging (MRI). OCT uses light waves (near-infrared domain) to form distinct, layered cross-sectional images [2].

In depth scan (on the z axis) of the retina at singular point are called called 'A-scan' resulting 1-D signal, see fig. 1. A high number of A-scans compose a single 'B-scan' (on the x axis); higher density of the A-scan results in higher resolution of the B-scans. Three dimensional images are composed of multiple B-scans placed on the y axis. The structure of the retina in three dimensional images are easily displayed on SD-OCT (spectral domain OCT), analyzing the spectrum of the reflected light into the retina.

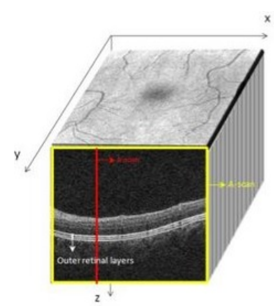

Fig. 1. Example of 3-D OCT scan on retina, with A-scans on z direction and B-scans on x-z direction [3]

Main usage of OCT scans is to determine thickness of the retina and the ability to observe the anterior segment of the eye, being fundamental in the measurement of precise intraocular lenses. The functionality of an OCT is similar to that of a medical ultrasound machine, both machines send a direct wave throw the tissue, the reflected waves are analyzed and the depth is determined based on the delay of measured wave. OCT uses an interferometer to split the light in the sample and to the reference arm. The base concept for OCT is the principle of low-coherence interferometry.

Fundamental for OCT interpretation, both quantitative and qualitative data are essential to fully evaluate OCT scans [4]. Qualitative interpretation is mainly fulfilled by the medical staff, in three important stages:

- Registration. This involves the correct order of scans, requiring the anatomic area of interest to be scanned similarly for future references.
- Sampling errors. This is mostly influencing singular scans, where the correct pathology may be missed in this

case. As a result, multiple scans of the macula represent a key factor for qualitative data.

- Subjective evaluation. Individualization of the macular scans will result from lack of accurate qualitative data. Supplementary, the discrepancy between improvement and deterioration of successive areas of the macula are difficult to measure.

Nevertheless, quantitative data from OCT scans is done by the software. The software will provide information regarding the inner and outer margin of the retina or sub-layers. This process is usually named segmentation, resulting from this process the retina thickness and/or the volume. The corresponding value is used to determine the normality of the retina or to determine the evolution or regression of a disease. For this purpose is important to utilize the same machine, since different software installed on different OCT machines could provide different layers and resulting in inconsistency in the retina layer measurement for same patient in the same day checkup/visit. Since quantitative data is represented by the software on the OCT machine, even in modern instrumentation, can result in errors.

II. Related work

Much effort has been done in the recent years to help the health system to overcome over-burned patient-care system, diagnose and proper treatment become error-prone and time-intensive [5] using AI. The process has been mainly focused on computer aided diagnostic (CAD) strategies. Many applications used for ophthalmology are focusing on one of the following categories: optic disc segmentation, retina layer segmentation, retinal blood vessel segmentation, red lesion detection, disease classification. Disease classification has the main focus in this study.

Grassmann et al. [6], Burlina et al. [7], Burlina et al. [8] utilizes different datasets composed of fundus images to determine AMD severity in the eye utilizing either deep learning based on classification or universal deep feature combined with transfer learning. This studies have reached an accuracy above 94.3 %. Treder et al. [9] utilized a dataset composed of SD-OCT images to detect Age-related macular degeneration (AMD) using deep learning, with a successful rate of 100%. In studies from Zhixi et al. [10], Asoaka et al. [11], Chen et al. [12], Chen et al [13], Chai et al. [14], Muhammad et al. [15] and Fu et. al. [16] using deep learning techniques, accuracy above 90% have been achieved to determine glaucoma detection with the use of either fundus or OCT dataset. Diabetic Macular Edema(DME), a complication from diabetes that causes fluid to accumulate in the macula, resulting in blurry or wavy vision, has been successfully classified using OCT images by Vahadan et al. [17], Varadarajan et al [18] and Perdomo et al. [19]. using different CNN (convolutional neuronal network) arhitectures.

A more complex dataseet has been used, in the study provided by Kermany el al. [20]. A total of 108312 OCT images have been used to train the dataset, having four categories: CNV, DME, Drusen, and Normal. The total number of images result from a number of 4868 patients. The study is based on transfer learning, where the model can recognize the distinguish features of images, such as eye diseases from OCT image. This study used six experts to label the total number of images into the desired categories. The results of the trained model was compare to those of the specialist, to determine the accuracy of the model. Furthermore, this algorithm has been used to test cohort of pediatric chest radiographers that validates the technique over multiple image modalities.

III. Proposed work

The interpretation of the optical coherency tomography scan requires certified specialist to determine if there is an abnormality in the retina. The specialists use a healthy retina as the reference point to formulate a diagnostic. The process of diagnose is time consuming and expensive, considering the fact that for each patient a medical assistant or doctor has to study each individual B-scans. Resulting in long time waiting for a result or diagnosis. Common treatable blinding retina diseases can nowadays be diagnosed and supervised using artificial intelligence (AI) on optical coherency tomography scans. Moreover, challenging cases for humans, has the potential to provide a precise assisted diagnosis's process, with a correct and precise diagnostic. The specialist requires individual study of the retina, resulting in long waiting time for a diagnosis. On the contrary, while using AI algorithms, huge amounts of optical coherency tomography scans are classified in short time, almost instantaneously, with a precise diagnose. Moreover, multiple patients can be receive a fast diagnostic in few minutes.

The goal of this study, to mimic the knowledge of specialist when diagnosing diseases of the retina. For this purpose AI is the relevant method used. A dataset with OCT images is used to train the chosen model. TensorFlow, Keras and Python are key software that are used to train the model. The following algorithms have been used for training: convolutional neuronal network (CNN) with 7 layers, MobileNet, GoogLeNet, ResNet18, ResNet101, InceptionV3, VGG16. The system can be observed in Fig. 2. Raspberry PI 4 has ARM Cortex-A72 processor of 1.5GHz 64-bit quad-core CPU [21]. This processor is sufficient to be utilize for many applications, but limited when it comes to big data. For this reason, the trained model can be further imported into Raspberry Pi 4, a powerful, portable, tiny and affordable broad [22], to predict diseases in the retina. Training of the model is a process that is necessary only at the incipient phase. While, many OCT images can be predicted using the loaded model on the Raspberry Pi 4 board. To successfully predict the presence of abnormalities or presence in the retina, the following libraries have to be installed on the board: *OpenCV* , *TensorFlow-Lite* , *TensorFLow* , *TensorFlow*

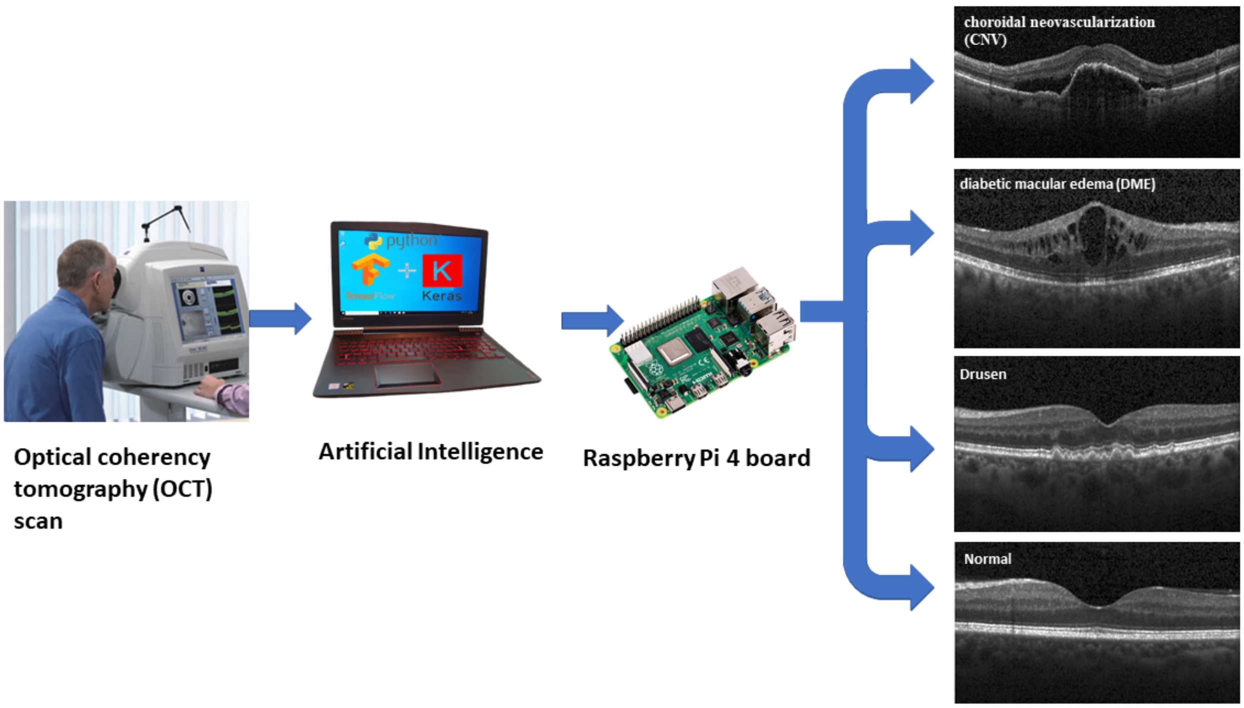

Fig. 2. Schematic view of OCT process using portable platform.

Addons , Pytorch , TorchVision, matplotlib, keras, scikit-learn.

IV. DATASET

To train each of the chosen algorithms, an open-source dataset provided by Kermany et al. [20] has been used, improved with our contribution (see Acknowledgements). The dataset is labelled into four main categories: Normal retina with preserved foveal contour and absence of any retinal fluid/edema, presence of choroidal neovascularization (CNV), diabetic macular edema (DME) or multiple drusen in the retina. The dataset used for training is composed of 8000 images equally divided between the four classes, as it can be observed in fig. 3. A separate dataset has been used to test the accuracy of the trained model imported on the Raspberry Pi 4 board.

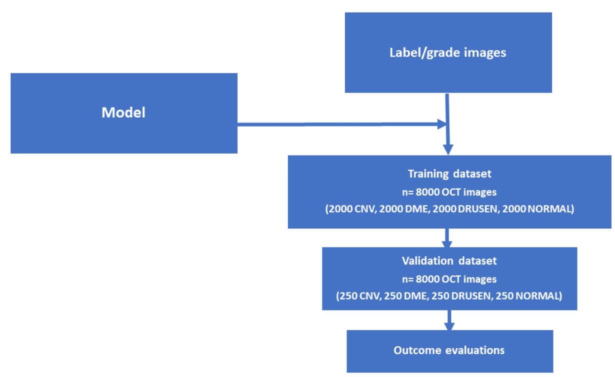

Fig. 3. Schematic view of OCT process using portable platform.

V. RESULTS

Deep learning algorithms have been successfully trained using the provided dataset described in section IV. The Raspberry Pi 4 board has the main function as 'desktop computer'. The trained OCT model is loaded on the board. In the process of diagnosing a patient, data coming directly from the OCT machine will predict as whether the patient has abnormalities in the retina. Using the functionality *EarlyStopping* from Keras library, result in the stop of the train when no improvement has been provided after multiple losses in consecutive epoches.

Supplementary, for the study some of the most utilized algorithms have been tested. To visualize the accuracy of the used algorithms, confusion matrix have been used to display the prediction versus the true label of the class. On the x-axis the prediction is displayed, while on the y-axis the true label is defined. On the diagonal elements the correct prediction is provided. The accuracy of this algorithms based on each class and as a total, can be observed in Table I and are discussed below.

TABLE I
RESULTS OF APPLIED MACHINE LEARNING ALGORITHMS ON DATASET

Algorithm	Accuracy CNV	Accuracy DME	Accuracy DRUSEN	Accuracy Normal	Accuracy overall
LeNet-5	64.4 %	18 %	35.2 %	82%	50 %
AlexNet	94 %	76.8 %	45.6 %	96.4 %	78 %
ZFNet	98.2 %	86.4 %	75.2 %	82.8 %	85 %
CNN7	95.6 %	86.8 %	92.4 %	100 %	94 %
MobileNet	94.8 %	91.2 %	95.6 %	98.4 %	95 %
VGG16	98.8 %	96.4 %	90.4 %	99.6 %	96 %

A. LeNet-5

B. AlexNet

C. ZFNet

D. CNN7

E. MobileNet

F. VGG16

VI. CONCLUSIONS

ACKNOWLEDGMENT

We thank Dr. Horea Demea from OFTAREVIEW clinic, for providing a new set of images from each category. The provided images from the provided dataset share similar characteristics to the train and has been used to test the accuracy of the applied machine learning algorithms. We intend to include additional classes in the dataset for further studies.

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