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Data Augmentation For Improving Proliferative Diabetic Retinopathy Detection In Eye Fundus Images Using Machine Learning Techniques

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Abstract: Nowadays, some of the most common causes of visual impairment and blindness are diabetic retinopathy, glaucoma, hypertension and macular degeneration. Therefore computer aided automated diagnosis approaches have great potential in clinical to accurately detect DR in a short time which can further help to improve the screening rate of DR and reduce the number of blindness. For a deep learning model, the most important parts that should be focused on are data set, network architecture and training method. Before being used to train our model, fundus images data set obtained from public resources is preprocessed and segmented. In the proposed system OD (Optic Disk) detection based on structured learning which belongs to a supervised method to avoid making assumptions. The proposed method utilizes the edge information of the fundus image to detect the OD. Finally the deep neural network (DNN) classifier is used to check whether the fundus image is cancerous or non-cancerous.

Keywords: visual impairment, diabetic retinopathy, glaucoma, hypertension, macular degeneration, structured learning, deepneural network,

I.INTRODUCTION

High pace rise in Glaucoma, an irreversible eye disease that deteriorates vision capacity of human has alarmed academia-industries to develop a novel and robust Computer Aided Diagnosis (CAD) system for early Glaucoma tic eye detection. The main root cause for glaucoma growth depends on its structural alterations in the retina and is very much essential for ophthalmologists to identify it at an initial period to stop its progression. Fundoscopy is among one of the biomedical imaging techniques to analyze the internal structure of retina. Recently, numerous efforts have been made to exploit Spatial-Temporal features including morphological values of Optical Disk (OD), Optical Cup (OC), Neuro-Retinal Rim (NRR) etc to perform Glaucoma detection in fundus images[1]. Here, some issues like: suitable pre-processing, precise Region of Interest segmentation, post-segmentation and lack of generalized threshold limits efficacy of the major existing approaches. Furthermore, the optimal segmentation of OD and OC, nerves removal from ODor OC is often tedious and demands more efficient solution. However, these approaches cumulatively turn out to be computationally complex and time-consuming. As potential alternative, deep learning techniques have gained wide-spread attention, especially for image analysis or vision technologies.

With this motive, in this paper, the authors proposed a novel Convolution Stacked Auto-Encoder (CSAE) assisted Deep Learning Model for Glaucoma Detection and Classification model named

Glaucoma. Unlike classical methods, Glauconitic applies Stacked Auto- Encoder by using hierarchical CNN structure to perform deep feature extraction and learning. By adapting complex data nature, and large features, Glaucoma was designed with three layers: convolution layer (CONV), Max-pool layer (MP) and two Fully Connected (FC) layers where the first performs feature extraction and learning, while second exhibits feature selection followed by the reduction of spatial resolution of the individual feature map to avoid large number of parameters and computational complexities. To avoid saturation problem in this work, by marking an applied dropout as 0.5. MATLAB based simulation-results with DRISHTI-GS and DRION-DB datasets affirmed that the proposed Glaucoma model outperforms as compared to other state-of-art techniques: neural network based approaches in terms of accuracy, recall, precision, F-Measure and balanced accuracy[2].

The exponential rise in technologies has broadened the horizon for different applications or systems to make human life more efficient, productive and quick decisive. Amongst the major innovations, healthcare sector is the one demanding more attention to make diagnosis more efficient and precise. In the last few years, Computer Aided Diagnosis (CAD) systems have gained worldwide attention across academia-industries to develop more efficient solution; however increase in complexities, symptoms variations, and other key factors such as localized disease traits, different demography etc confine efficiency of the major existing solutions. Considering an example, Glaucoma, which is a type of irreversible eye-disorder or disease, has emerged as one of the most dangerous eye disorder globally that damages optic nerve and degrades vision capacity. However, its growth patterns, size and shape has always been different for different locations or people. In other words, the morphological traits of Optical Cup (OC) and Optical Disc (OD) of a Chinese used to be different than the one from Algeria or Africa. In such case developing a universally applicable model becomes must for accurate or precise Glaucoma detection. Recent study revealed that Glaucoma is the most causative factor for blindness that might reach up to 20 million patients by or before 2020. In majority, Glaucoma often remains undetected for long time that makes it imperceptible across the early stages. Consequently, we term it as the "silent theft of sight". In major cases of Glaucoma, a person doesn't feel any pain or similar symptoms and therefore it can be detected only when it reaches to the advanced stage with more severe symptoms. As already stated, Glaucoma being an irreversible eye-damage disease affects the optical nerve responsible for accommodating information from the eye to the brain and causes blindness and ocular hypertension[3]. Unlike other eye diseases like Myopia or Cataracts, Glaucoma disrupts vision capacity completely and therefore there is the inevitable need to develop a robust CAD solution for precise and early Glaucoma detection and classification (for severity assessment). Typically, there are three dominant methods for Glaucoma detection; Intraocular Pressure (IOP) measurement, Function-Based Visual Field Test (FBVFT), and Optic Nerve Head (ONH). Though, IOP signifies a significant risk factor; it can't be universally robust to detect Glaucoma for different stages with varied clinical-measurement values. On the other hand, FBVFT demands very specific parametric and sophisticated tools which are costly a commonly not available in major primary healthcare centers[4]. ONH examination is an expedient approach to identify Glaucoma in its early stage, and is contemporarily performed by professional and skilled Glaucoma specialists. Undeniably, manual ONH process is time consuming and even costly. In major ONH methods different morphological or clinical parameters like Vertical Cup to Disc Ratio (CDR), Rim to Disc Area Ratio (RDR), NRR, and Disc

Diameter are used to detect and characterize Glaucoma in the fundus images [5]. CDR based methods have been extensively used where a larger CDR signifies higher Glaucoma-risk.

II. Glaucoma Diagnosis with Machine Learning

This study aimed to develop a machine learning-based algorithm for glaucoma diagnosis in patients with open-angle glaucoma, based on three-dimensional optical coherence tomography (OCT) data and color fundus images. In this study, 208 glaucomatous and 149 healthy eyes were enrolled, and color fundus images and volumetric OCT data from the optic disc and macular area of these eyes were captured with a spectral-domain OCT (3D OCT-2000, Topcon). Thickness and deviation maps were created with a segmentation algorithm. Transfer learning of convolution neural network (CNN) was used with the following types of input images: fundus image of optic disc in grayscale format, disc retinal nerve fiber layer (RNFL) thickness map, macular ganglion cell complex (GCC) thickness map, disc RNFL deviation map, and macular GCC deviation map. Data augmentation and dropout were performed to train the CNN. For combining the results from each CNN model, a random forest (RF) was trained to classify the disc fundus images of healthy and glaucomatous eyes using feature vector representation of each input image, removing the second fully connected layer. The area under receiver operating characteristic curve (AUC) of a 10-fold cross validation (CV) was used to evaluate the models. The 10-fold CV AUCs of the CNNs were 0.940 for colour fundus images, 0.942 for RNFL thickness maps, 0.944 for macular GCC thickness maps, 0.949 for disc RNFL deviation maps, and 0.952 for macular GCC deviation maps. The RF combining the five separate CNN models improved the 10-fold CV AUC to 0.963. Therefore, the machine learning system described here can accurately differentiate between healthy and glaucomatous subjects based on their extracted images from OCT data and color fundusimages. This system should help to improve the diagnostic accuracy in glaucoma. Glaucoma is a chronic, neurodegenerative ocular diseasecharacterized by optic neuropathy and visual disturbance that corresponds to optic disc cupping and optic nerve fiber degeneration. Lowering the intraocular pressure (IOP) is an effective, evidence- based treatment for open-angle glaucoma (OAG).This treatment requires early diagnosis and adequate IOP control to maintain a good quality of life. This becomes even more important in today's aging societies. Generally, glaucomatous structural changes precede functional changes. Therefore, the early diagnosis of glaucoma relies on detecting these structural changes. The most basic diagnostic tool for glaucoma diagnosis is the analysis of color fundus images, which can identify glaucomatous optic neuropathy, including rim thinning and notching, undermining, cupping, a high cup-to-disc ratio, disc hemorrhage, and retinal nerve fiber layer (RNFL) defects. Another powerful tool is optical coherence tomography (OCT), which can be used to describe glaucoma both qualitatively and quantitatively. OCT, which targets the optic disc and macular area, can reveal preperimetric glaucoma with high sensitivity

Input image Preprocessing

Segmentation

Normal/Abnormal

Training &Testing
Classification

Feature Extraction

Fig.1 Simulink blocks showing methodology

and specificity. For glaucoma diagnosis, the power of different OCT scan parameters, such as disc topography, circumpapillary RNFL thickness (RNFLT), macular RNFLT, ganglion cell layer plus inner plexiform layer thickness, and ganglion cell complex (GCC) layer thickness, differs with variations in glaucomatous structural changes. Therefore, for diagnosing all types of glaucoma, it is best to use OCT data both from the disc and the macula.

III. RESULT AND DISCUSSIONRGB Color Model:

A representation of additive color mixing. Projection of primary color lights on a screen shows secondary colors where two overlap; the combination of all three of red, green, and blue in appropriate intensities makes white.

Fig.2 RGB color model

The RGB color model is an additive color model in which red, green, and blue light is added together in various ways to reproduce a broad array of colors. The name of the model comes from the initials of the three additive primary colors, red, green, and blue. The mainpurpose of the RGB color model is for the sensing, representation, and display of images in electronic systems, such as televisions and computers, though it has also been used in conventional photography.

CONVERTING COLOR TO GRAYSCALE

Conversion of a color image to grayscale is not unique; different weighting of the color channels effectively represents the effect of shooting black-and- white film with different-colored photographic filters on the cameras.

To convert any color to a grayscale representation of its luminance, first one must obtain the values of its red, green, and blue (RGB) primaries in linear intensity encoding, by gamma expansion. Then, add together 30% of the red value, 59% of the green value, and 11% of the blue value (these weights depend on the exact choice of the RGB primaries, but are typical). Regardless of the scale employed (0.0 to 1.0, 0 to 255, 0% to 100%, etc.) the resultant number is the desired linear luminance value; it typically needs to be gamma compressed to get back to a conventional grayscale representation.

This is not the method used to obtain the luma in the YUV and related color models, used in standard color TV and video systems as PAL and NTSC, as well as in the L*a*b color model. These systems directly compute a gamma-compressed luma as a linear combination of gamma-compressed primary intensities, rather than use linearization via gamma expansion and compression.

To convert a gray intensity value to RGB, simply set all the three primary color components red, green and blue to the gray value, correcting to a different gamma if necessary.

GRAYSCALE AS SINGLE CHANNELS OFMULTI CHANNEL COLOR IMAGES

Color images are often built of several stacked color channels, each of them representing value levels of the given channel. For example, RGB images are composed of three independent channels for red, green and blue primary color components; CMYK images have four channels for cyan, magenta, yellow and black ink plates, etc.

Here is an example of color channel splitting of a full RGB color image. The column at left shows the isolated color channels in natural colors, while at right there are their grayscale equivalences:

The reverse is also possible: to build a full color image from their separate grayscale channels. By mangling channels, using offsets, rotating and other manipulations, artistic effects can be achieved instead of accurately reproducing the original image.

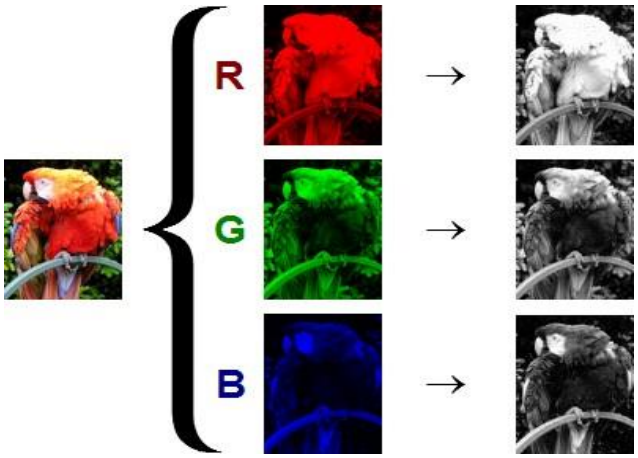
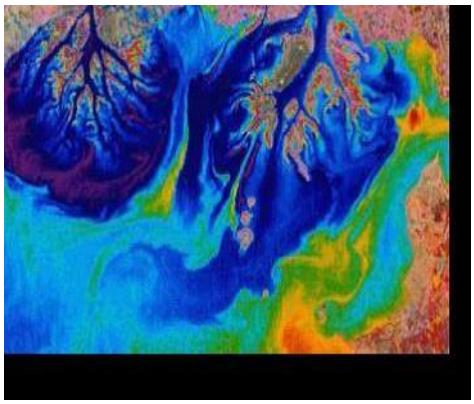


Fig.3 Composition of RGB from 3 Grayscale images

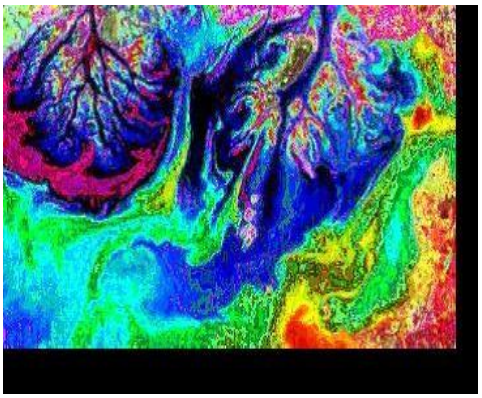
HISTOGRAM EQUALIZATION OF A COLORIMAGE:

Figure shows a color image with 768 x 512 pixels and 16 levels for each band. As a result of the color histogram equalization, Figure 3 shows more diversity in color than. Due to lack of space, the three-dimensional histogram is not depicted here. In fact, itis equalized uniformly. It took 412.6 seconds to equalize the histogram with nonzero values at 1501 colors out of 4096. Consecutive probabilities in

the histogram would be further investigated. The results ofthe histogram equalization for two color images are displayed.



(a) Original image



(a) Color-equalized image Fig.4 Histogram equalization of a color image.

IV. CONCLUSION

The proposed method in this paper employs structuredlearning to capture the OD edge information. Because the proposed algorithm belongs to supervised methods, the trained edge detector plays an important role in the performance of the proposed method. The proposed method utilizes the edge information of the fundus image to detect the OD. It is different from the traditional method which applied the traditional edge detector, such as Sobel edge detector, to capture the edge information. Circle Hough transforms is applied to approximate the boundary of OD.Finally Finally thedeep neural network (DNN) classifier is used to check whether the fundus image is normal or abnormal.

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