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Age-related Macular Degeneration detection using deep convolutional neural network

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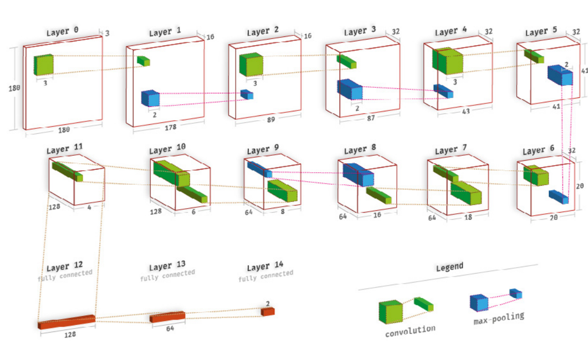
HIGHLIGHTS

- Automated detection of age-related macular degeneration(AMD) with fundus images.
- A 14-layer convolutional neural network is employed.
- Trained and tested on 402 normal and 708 AMD images.
- Achieved an average accuracy of 95.45% with ten-fold cross validation.
- Achieved an average accuracy of 91.17% with blindfold.

GRAPHICAL ABSTRACT



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ABSTRACT

Age-related Macular Degeneration (AMD) is an eye condition that affects the elderly. Further, the prevalence of AMD is rising because of the aging population in the society. Therefore, early detection is necessary to prevent vision impairment in the elderly. However, organizing a comprehensive eye screening to detect AMD in the elderly is laborious and challenging. To address this need, we have developed a fourteen-layer deep Convolutional Neural Network (CNN) model to automatically and accurately diagnose AMD at an early stage. The performance of the model was evaluated using the blindfold and ten-fold cross-validation strategies, for which the accuracy of 91.17% and 95.45% were respectively achieved. This new model can be utilized in a rapid eye screening for early detection of AMD in the elderly. It is cost-effective and highly portable, hence, it can be utilized anywhere.

1. Introduction

The world is currently facing an aging population with approximately 962 million people aged 60 years or above [1]. This number

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is expected to double to 2 billion people by 2050 [1]. With such a rapid growth in aging population, it is inevitable that the Global Burden of Disease (GBD) among the elderly increases too [2]. The rise of GBD is associated with higher medical costs and lower quality of life affecting not only the aged people but also their caregivers and the health economy [3]. Co-morbidities in the aging population often cause further delay in early diagnosis of treatable conditions. Therefore, there is an unmet need to develop simple, cheap and portable diagnostic and analytical tools to allow early diagnosis and prompt referral for treatment [4].

Age-related Macular Degeneration (AMD) is one of the conditions commonly faced by the elderly. It is the prime cause of vision loss in elderly (>50 years old) [5–8]. AMD is a chronic eye condition that affects the central vision of the eye [9]. It is due to the degeneration of the macula, the central part of the retina that subserves clear and sharp vision [9].

Typically, AMD can be characterized by four stages (no, early, intermediate, and advanced) [10]. No AMD is graded when there is no or a few small drusen (macular yellow deposits) present. Early AMD is graded if there is small to medium-sized drusen [10]. Intermediate AMD is characterized by at least one large-sized drusen or a handful of medium-sized drusen with or without pigmentary changes. Advanced AMD may be dry or wet types. Dry AMD is graded as Geographic Atrophy (GA) when there is loss or atrophy of the retinal pigment epithelium at the macula. This atrophic area progresses slowly to the center of the macula. Center-involving GA leads to an irreversible loss of vision [10]. The wet AMD, on the contrary, is more sudden in onset and progresses rapidly. Wet AMD occurs as a result of an abnormal growth of blood vessels beneath the retina, that may leak or bleed causing a rapid decline in vision [10].

There are no symptoms present at an early stage of AMD. Some symptoms such as blurred or distorted vision may appear in intermediate while visual acuity invariably deteriorates in advanced AMD [9]. Timely detection and treatment impede further deterioration in vision in wet AMD. Hence, it is of utmost importance for an early diagnosis of wet AMD to prevent progressive visual impairment in the elderly. AMD can be diagnosed using fundus photography. Fundus photography is the preferred tool for classifying the severity of AMD.

However, the visual interpretation of fundus images can be subjective and is prone to interobserver variabilities. Thus, a Computer-Aided Diagnosis (CAD) system is proposed to aid in the objective and reliable assessment of fundus images. A lot of studies have been done on the automated identification of AMD fundus images. However, no attempt of implementing deep learning solutions has so far been proposed to support AMD detection.

Therefore, a fourteen-layer deep Convolutional Neural Network (CNN) is proposed to automatically classify the fundus images into normal or AMD classes in this work. In contrast to other studies, no handcrafted features are required. Instead, fundus images are fed into the proposed model and a diagnosis is given almost instantaneously.

CNN is a subclass of a multilayer Neural Networks (NN) and it is one of the architectures in deep learning. It is a computational model based on the biological neural networks in the human brain [11]. CNN has been gaining recognition in analyzing medical image data [11,12]. Some applications of CNNs to analyze retinal images have already been published. For instance, van Grinsven et al. [13] applied CNN to identify hemorrhages in fundus images. They applied a nine-layer CNN model in their work. Also, a seven-layer deep CNN was employed to concurrently locate and segment fovea, optic disk, and vasculature from fundus images [14]. The high accuracy performance of the proposed CNN model highlights the potential capabilities of CNN in CAD systems. CNNs can also be applied in other CAD applications including the detection of arrhythmia [15], coronary artery disease [16], and myocardial infarction [17]. Furthermore, CNN models have revealed outstanding recognition ability in visual recognition assignments [12,18].

The performance of the model was evaluated using the blindfold and ten-fold cross-validation strategies, for which the accuracy of 91.17% and 95.45% were respectively achieved. This new model can be utilized in a rapid eye screening for early detection of AMD in the elderly. It is cost-effective and highly portable; hence, it can be utilized anywhere. The design the deep learning model for the dry and wet AMD images is the novelty of this paper.

2. Data

The data used in this work were acquired from the Ophthalmology Department of Kasturba Medical College (KMC), Manipal, India. We have obtained ethics approval to collect the fundus images from Kasturba Medical Hospital, Manipal to conduct this study. We evaluated 402 eyes with normal fundus, 583 retinal images with early, intermediate AMD, or GA and 125 retinal images with evidence of wet AMD.

The images collected were acquired using Zeiss FF450 plus mydriatic fundus camera with the image resolution of 2588×1958 pixels. Examples of normal and AMD (dry and wet) fundus image can be seen in Fig. 1.

3. Methods

The architecture of the proposed model is listed in Table 1. The proposed model has seven convolution layers, four max-pooling layers, and three fully-connected layers. Fig. 2 shows a graphical illustration of the proposed CNN model.

The CNN architecture is made up of convolution, pooling, and fully-connected layer [11,19]. The main purpose of the convolution operation is to pick up distinct features from the input fundus image. The convolution is performed with convolution filters (kernels) to generate feature maps [11,20]. The pooling operation reduces the output dimensionality and ensures a fixed output size. The max-pooling operation is performed in this study. This operation takes the highest value from each kernel, reducing the size of the feature maps. The stride (number of units the filter slides) for convolution and max-pooling is set at 1 and 2 respectively in this work. The fully-connected layer uses a softmax activation function for the output layer. The main purpose is to predict the input fundus image into normal or AMD classes.

Each image was rescaled to 180×180 dimension. The input layer which consists of size $180 \times 180 \times 3$ where each dimension represents height, width and channel respectively is convolved with 16 $3 \times 3 \times 3$ kernels to form layer 1. Then a max-pooling of 2×2 is performed. After which, a convolution is performed again in layer 2 with 32 $3 \times 3 \times 16$ kernels, followed by a 2×2 max-pooling operation to form layer 4. Once again, a convolution is applied on 32 feature maps in layer 4 to form layer 5. Then, a max-pooling is applied in layer 6. Then, convolution is performed again in layers 6, 7, and 8 before a max-pooling of size 2×2 is applied. Convolution is again applied to 64 feature maps in layer 9 and convolved again in layer 10 to produce $4 \times 4 \times 128$ number of neurons (layer 11). The neurons in layer 11 are fully-connected to 128 neurons in layer 12. Also, layer 12 is fully-connected to 64 neurons in layer 13 and fully-connected to layer 14 (the output layer) with an output of 2 neurons to represent normal and AMD classes.