

THE DEVELOPMENT OF AN ACCURATE AND COMPUTATIONALLY FEASIBLE MOBILENETV2 ALGORITHM TO DIAGNOSE RETINAL DISEASES

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ABSTRACT

As of October of 2021, the World Health Organization reported there being at least 1 billion people worldwide with a preventable or treatable visual impairment. A significant portion of visual impairment is caused by retinal diseases, with 3.9 million people affected by Diabetic Retinopathy (DR), 7.7 million by Glaucoma, 93 million by Cataracts, and an unspecified number affected by AMD, Hypertension, and PM (World Health Organization, 2021). Along with these numbers comes the increased demand for reliable methods of diagnosis. Currently, the costs of equipment, ophthalmologist headcounts, and procedure duration in conventional approaches are all factors contributing to the need for more practical methods of diagnosis. As a solution, the MobileNetV2 deep learning algorithm was employed to accurately and efficiently assign diagnoses early on to patients with the use of fundus images. The categorical assignment capabilities of MobileNetV2 allowed for the identification of primary retinal diseases like Diabetic Retinopathy (DR), Age- Related Macular Degeneration (AMD), Glaucoma, Cataracts, Hypertension, and Pathological Myopia (PM). The solution was also trained to identify healthy patients and those with other conditions to decrease the chances of misdiagnosis.

Keywords: MobileNetV2, Fundus, Machine learning, retinal images, computer vision

1. Introduction

AMD causes central vision to blur because the macula, which is located at the back of the retina, undergoes deterioration. Thinning of the retina, the presence of drusen, pigment abnormalities, and the growth of abnormal blood vessels can indicate the onset of AMD (National Eye Institute,

2019). A Cataract is a clouding of the normally clear lens of the eye caused by the breakdown of proteins in the eye lenses, making one's vision look blurry, hazy, or less colored (Mayo Clinic, 2021). Glaucoma causes blind spots, tunnel vision, and even complete blindness and is caused by high pressure in the eye, which damages the optic nerve.

The progression of Glaucoma is commonly able to be determined by measuring the cup-to-disk ratio in fundus images (*Glaucoma Screening in Fundus Image - next Sight Retinal Imaging System*, n.d.). Hypertension causes microvascular damage in both the cerebral and retinal circulations, with potential thickening of the retina's blood vessels that, overtime, may cause permanent damage by limiting the retina's function and putting pressure on the optic nerve (Pranav Modi & Tasneem Arsiwalla, 2019). DR occurs when high blood pressure affects blood vessels in the retina and the macula, which can lead to central vision loss and blood vessel leaks between the eye lens and retina (*Diabetic Retinopathy | National Eye Institute*, 2019). PM is identified by increased short-sightedness that results from degenerative changes to the back of the eye that prevent light from being focused on the retina properly (Shah et al., 2016).

The most common conventional methods for the diagnosis of retinal diseases are Fluorescein Angiography (FA), Optical Coherence Tomography (OCT), and manual inspection of fundus images (Sheet et al., 2021). FA allows blood vessels in the eye to be viewed in detail through a microscope, which leads to fairly accurate diagnosis, but also may put patients at risk of possible allergic reactions due to the injection of fluorescein dye (*Fluorescein Angiography | Department of Ophthalmology*, 2020). OCT is a safe and reliable procedure that creates detailed maps of a patient's retina to help identify retinal diseases (Bazan, 2021). Fundus photography is considered very safe and uses a low-power microscope and camera to photograph a patient's retina (*Color Fundus Photography | Department of Ophthalmology*, 2019). FA usually takes about 10 to 20 minutes and has an average administration cost of \$905 (*Intravenous Fluorescein Angiography*, 2022). Although OCT usually lasts only 5 to 10 minutes, the equipment required for OCT is very expensive, between \$40,000 and \$150,000, and is therefore restricted in availability to potential victims of retinal diseases (Song et al., 2021). Fundus photographs were used in this project, as the procedure usually lasts only around 5 minutes and the price of administration is usually only \$30 to \$60 (Chou, 2011).

Although the FA and OCT methods paired with manual analysis are quite effective in theory, they are unfortunately subject to a chance of incorrect diagnosis by an ophthalmologist, which is commonly thought to be attributed to time constraints and a lack of appropriate training, among other factors. (Stuart, 2020). As a solution to this problem, various deep learning systems that aid in the diagnosis and monitoring of various eye diseases have been employed, such as those by Ting et al., who created a deep learning system capable of identifying DR, glaucoma, and AMD with areas under the curve of 93.6, 94.2, and 93.1%, respectively (Ting et al., 2017). The benefits

of the use of deep learning in ophthalmology are particularly evident in mass data analysis, which can aid in automated diagnosis and potential outcome predictions. Training and input data for this project was collected through fundus imaging, one of the most economical and least time consuming sample collection methods, making the created method notably efficient and affordable for the identification of the mentioned retinal diseases.

Our solution utilizes the Python programming language, open-source Keras software library, Numpy library, and tensorflow for model creation. The specific algorithm we employed was MobileNetV2; the entire program was written within the Google Colaboratory data science notebook, where an external GPU was leveraged.

Procedures

The MobileNetV2 algorithm was employed in this project due to its relatively lower computational expense with respect to accuracy (Sandler & Howard, 2018). This lower computational demand has allowed for its application in devices such as cellphones and microcontrollers. The algorithm was applied with the Keras deep learning library, which is integrated with the TensorFlow machine learning framework for fast numerical computation. The solution utilized Dense, MaxPooling2D, Dropout, and Conv2D type layers and the Adam type optimizer. Images from 4 datasets released on Kaggle were used for training, validation, and testing of the model; 20,087 images were used for training, 433 for validation, and 1,250 for testing. Two of the datasets feature fundus images of DR in various stages, while the other two contain fundus images of glaucoma, cataracts, AMD, hypertension, DR, PM, normal eyes, and other diseases/abnormalities.

Image preprocessing

For preprocessing, the images to be used for training and validating the model were altered from a 0-255 RGB scale to a 0-1 scale. Every image used was resized to 200x200 pixels. For the training, validation, and testing sets, 11 categories of images were determined by the model. The specific categories were proliferate DR, severe DR, wet AMD, hypersensitive retinopathy, mild DR, cataract, pathological myopia, moderate DR, dry AMD, glaucoma, and normal fundus images.

Training and Validating the model

The ReLU activation function was used for its benefits regarding backpropagation and solving the issue of gradient descent. Additionally, the softmax activation function was used to allow for multi-class classification. The categorical cross-entropy loss function was employed to evaluate the model and the accuracy of its predictions, and the Adam optimizer, which combines

RMSprop and Momentum, was used to optimize gradient descent and decrease training time.

Testing the model

The first iteration of the model had 4 epochs and yielded a learning rate of 0.0001, an accuracy of 0.8536, and a CV accuracy of 0.7644. The second iteration had 20 epochs, and yielded a learning rate of 0.00005, an accuracy of 0.9773 and a CV accuracy of 0.7667.

Metrics

The Keras library used allowed for evaluation of error with the “loss” variable included in each epoch output line. The “loss” variable used was a scalar value between 0 and 1 determined by categorical cross entropy. The loss value reached a minimum value of 0.1133 in the final product.

Conclusion

Using the MobileNetV2 algorithm, the model identified all condition categories and exhibited a final accuracy of 0.9773 and a loss of 0.1133. Our machine learning model offers a more efficient and cost-effective method of diagnosis to ophthalmologists when compared to currently available options such as FA, OCT, and manual review of fundus images. In terms of accessibility, the presented method allows more of the world population that lacks access to advanced equipment to receive a valid diagnosis.

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