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Glaucoma Disease Diagnosis from Retinal Fundus Images using Deep Learning Model

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***Abstract*—Glaucoma could be an incessant and irreversible eye malady that disables vision and quality of life. The main objective of this paper is to perform automatic disease detection of glaucoma using deep neural network. A complete convolutional neural network (CNN) system has been developed, with the help of which the glaucoma diagnosis can be easily detected. The VGG16 convolutional neural network (CNN) model is proposed for image classification from the Kaggle glaucoma fundus imaging dataset. A total of six layers were required for training this dataset, including five transform layers and one fully connected layer. By trending this model on the dataset we got 99.8% which is much better than the state of art algorithm. This technique can be used for automatic glaucoma detection.**

***Index Terms*— glaucoma; deep learning; convolutional neural network; fundus imaging.**

I. INTRODUCTION

Glaucoma is the leading cause of visual impairment worldwide and has no cure It can also lead to permanent blindness in the future if not caught at an early stage. Early detection can prevent future vision loss. As it is a major chronic eye disease that develops permanent blindness. Glaucoma is on the rise even in urban areas in recent years. A 2014 study estimated that the number of people with glaucoma worldwide would increase from 64.3 million in 2013 to 76 million in 2020 and 111.8 million in 2040 [1]. Deep learning is a subset of machine learning (ML) that uses artificial neural networks (ANN) with multiple layers to analyze complex data [2]. These algorithms are designed to learn from large datasets, which makes them particularly useful for medical image analysis. In the context of glaucoma detection, deep learning models can accurately detect glaucoma from retinal images, outperforming convolutional methods. Techniques such as convolutional neural network have gained prominence due to their ability to automatically extract features from images without the need for manual intervention. Retinal fundus images are very important in the diagnosis of glaucoma because they provide detailed information about the optic nerve and per papillary retinal nerve fiber layer (RNFL). These images reveal key features of glaucoma such as optic disc abnormalities, cup-to-disc ratio, and changes in retinal blood vessels. By training deep learning models on large datasets of inoculated fundus images, researchers may be able to detect glaucomatous disease at an early stage and prevent future damage. The effectiveness of deep learning in detecting glaucoma is well documented [3]. Several studies have demonstrated that CNN can achieve high accuracy rates exceeding 90% in glaucoma disease detection from retinal images. These models are trained using labeled datasets that include both normal and glaucomatous retinal images. The training process involves adjusting the parameters of the neural network to reduce the error between the predicted and actual results.

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The robustness of the model is enhanced using data augmentation methods. Feature extraction is an important component of deep learning models for glaucoma detection. Deep learning automatically identifies the most relevant features from raw image data. Subtle variations through this teaching can indicate the presence of disease. Transfer learning is particularly useful when the available dataset is limited because it allows the model to exploit knowledge gained from larger datasets, reducing the risk of overfitting while improving performance. Models like VGG16, ResNet50 and MobileNetV2 are employed in this context and these models have shown success in working with different image classification tasks. Figure1 shows the marked difference in OD between a healthy and a glaucomatous eye. Different stages of glaucoma can be identified by fig2. Therefore, eye training is important for detecting glaucoma. Eye training process is considered time-consuming and tedious due to each patient checkup. This study aims to improve classification accuracy by automatically classifying photos of normal and glaucoma eyes based on fundus images. Increased accuracy requires important research and selection of glaucoma image classification criteria that are more specific and sensitive than currently used criteria.

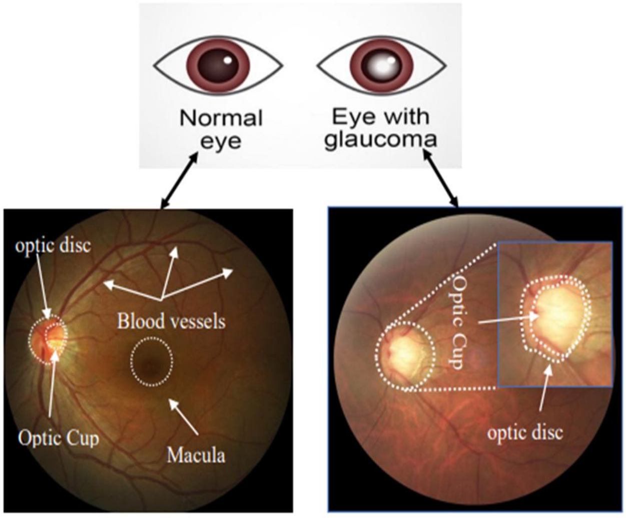

Figure 1. Images of a healthy retina (left-side) and one with glaucoma

Figure 2. Grading of glaucoma diseases- (a) Healthy OD; (b) Mild Glaucoma; (c) Moderate Glaucoma and (d) Severe Glaucoma.

II. Background

Several issues related to the effective use of imaging algorithms for ocular disease diagnosis were proposed in their study by the author [7-8], including image registration, fusion, segmentation, pattern matching, feature extraction, and image classification. A MATLABbased algorithm for mirror detection using Artificial Neural Networks (ANN) has also been developed [9]. Fuzzy logic was used by [10] to diagnose glaucoma. The feature identification and further classification are greatly reduced by the Randomized Hoff transformation. A 96% eradication rate was achieved using this method [5-6]. The detection of the optic disk is considered an important diagnostic feature of glaucoma, according to the authors of [11] who worked on optic disk detection and blood vessel density, changes in color intensity. Any error in the test can lead to an incorrect diagnosis. In [12], a deep learning method aimed at RNFL detection was described, whereas, in [13], a CNN-based method for atrial fibrillation detection was propose. A ResNet-based CNN method that improves glaucoma detection performance was described by other [14]. The usefulness of glaucoma detection is greatly reduced by the inconsistencies and large areas of redundancy in the images of the fundus dataset, thus making the model proposed in [15] less efficient. The analysis of the cornea was automated using a strong roots network (CNN) architecture obtained by the authors in [16]. Convolutional Neural Network (CNN) models have a multi-layer architecture that belongs to the class of deep learning algorithms. In that study, the authors make a clear distinction Glaucoma and non-glaucoma systems according to chronological order representation of features on CNN models. Six different layers of the CNN model were used, which were divided into four variable layers with two fully overlapping. The analysis on the ORIGA and SCES data sets was led to by AUC values of 0.8321 and 0.887 for the diagnosis of glaucoma retinopathy, respectively. The best results compared to state-of-the-art systems were achieved by the developed system, as reported by the authors. The deep-learning (DL) algorithm was developed in [6] to detect glaucoma eye disease by extracting various features, such as 52 total deviation, mean deviation, and model standard deviation values. The DL classifier was used by the authors as a deep feed-forward neural network (FNN). The DL classification was combined by the authors with other older machine learning classifications such as random forests (RF), gradient growth, support vector machine, and neural networks (NN). A deep clustering solution for glaucoma detection was presented by the authors. It was reported by the authors that 92.5% of the AUC value was obtained by deep FNN classification [4].

III. METHODS

For the classification of glaucoma images from normal images, even with the presence of early glaucoma images, the entire set of 6290 images is divided into 5000 training, 540 validation, and 750 test data. The test dataset is about 30% of the total dataset. The remaining dataset was split to about 80% training and 20% validation datasets.

TABLE I. SAMPLE NUMBER FROM DATASET

	NRG	RG	Total
Entire Data	3045	3245	6290
Training Data	2500	2500	5000
Validation Data	270	270	540
Test Data	275	475	750

A. Logistic Classification

Since fundus images are color images, they consist of three dimensional arrays (150 x 150 x 3). The images were flattened into one dimensional array of 1×(150×150×3) for logistic regression. A single layer of weights was used to produce logits, the sigmoid function was applied to obtain the probability of being classified as a NRG or RG image. These profanities are compared to a hot encoded level and the loss is calculated using the crossentropy. A gradient descent optimizer with a learning rate of 0.5 is used for optimization. The model is built using Google's Tensor Flow deep learning framework.

B. Convolutional Neural Network(CNN)

Data Augmentation

Because the images had a small amount of data, we applied enhancement to eliminate the overfitting in each image. Each images is cropped around it to produce images with a fixed size of 224 x 224. This cropping was repeated after image inversion, resulting in 10 images per image. Desperate enhancement can help eliminate overfitting by presenting an image from different angles to the computer to help make decisions.

Training Model

For transfer learning, we used a VGG16 pretrained model, which involves training our data using a pre-defined (trained) model already. We changed the final classification position of the VGG16 model to suit our classification needs, and then optimized it with our data. RMSprop optimizer for high spread, adaptive learning rate method, was used as the optimization function, while cross entropy was used as the loss function. Two convolutional levels with patch sizes of 2020 and 4040 and depths of 1 stride, 64 and 128 are used. Maximum pooling was used, with patch sizes of 22 and 2 feet. Two hidden layers, with 128 and 256 hidden units, were used as fully connected layers. A dropout rate of 0.5 was used at the convolutional and fully connected levels to prevent overfitting. ReLu (Rectifier Linear unit) was used as the operating unit. For backpropagation, crossentropy was used as a loss function and RMSprop optimizer was used as an optimization function. The model has been trained for 10 epochs, which a batch size of 32.

IV. Experiment Result

For evaluation of our proposed method, we have calculated the accuracy. Precision refers to the degree to which the calculated results agree with the ground truth. The evaluation of our proposed method is compared with [6-17] in which the author calculated the accuracy and the best prediction value as 95.0%,92.5% and 90.91%, respectively. Our proposed approach uses VGG16 which is a more efficient neural network architecture to classify the images in Kaggle dataset. The plot of Training accuracy and Validation accuracy, Training loss, and Validation loss have also been plotted in Figure 3 and Figure 4 respectively.

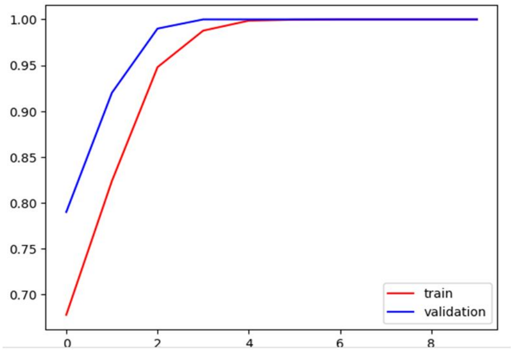

Fig3. Training and Validation Accuracy

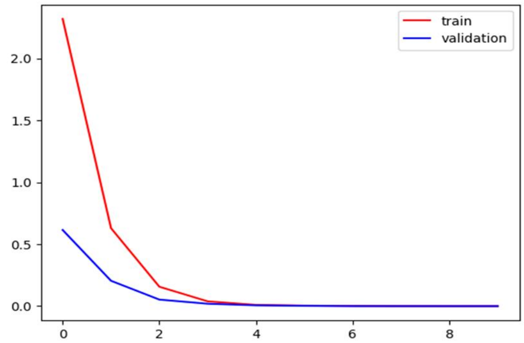

Fig.4 Training and Validation Loss

IV. Conclusion

Glaucoma is called a chronic eye disease that causes blindness and is an irreversible global disease. There is a need to automate this task and develop robust and effective computer-aided tools for glaucoma diagnosis. In this paper, we have presented a cost-effective digital algorithm that is able to detect glaucoma better than previous methods and the performance proposed in VGG16 is quite close to the ophthalmologist enabling Faster and cheaper patient treatment. This algorithm attains the accuracy of 99.8% on the classification of glaucoma infected eye sample. These test results are more accurate compared to previous CNN methods. This method can be used for quick and efficient assessment.

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