IMPACT: International Journal of Research in Applied,
Natural and Social Sciences (IMPACT: IJRANSS)
ISSN (P): 2347–4580; ISSN (E): 2321–8851
Vol. 12, Issue 4, Apr 2024, 1–10

GLAUCOMA DETECTION USING MACHINE LEARNING

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Received: 16 Apr 2024 **Accepted:** 24 Apr 2024 **Published:** 30 Apr 2024

ABSTRACT

Glaucoma is the leading cause of irreversible blindness and disability worldwide. Nevertheless, the majority of patients do not know that they have the disease and detection of glaucoma progression using standard technology remains a challenge in clinical practice. Fund us evaluation is an eye exam that helps both ophthalmologists and non-ophthalmologists to provide vital diagnostic information about Glaucoma.

This disease is considered an irreversible disease that results in vision deterioration. If treated early, it is possible to slow or stop the progression of the disease with medication, laser treatment, or surgery. The goal of these treatments is to decrease eye pressure. Content-based image analysis and computer vision techniques are used in various health- care systems which are adapted in our work to detect Glaucoma.

Damage manifests as a progressive shift in vision followed by vision loss. The treatment options for glaucoma include eye drops, surgeries such as laser therapy, filtering surgery, laser trabeculoplasty, and a trabecular bypass stent.

We use Transfer learning to train and screening the InceptionResNetV2 model for detection of glaucoma by using structural and functional tests which gives maximum accuracy compared to other CNN models by understanding the advancements in the particular area. In the proposed system which provides the detection accuracy of 88% in true positive and false positive in order to determine the Glaucoma in the eyes.

Since the present hardware used by the hospitals are fixed and expensive, we use an easy-to-use web app. It helps the patient to view the result from any part of the world.

KEYWORDS: *Glaucoma diagnosis, Deep learning, Image classification, Transfer learning, Inception-ResNet-V2.*

INTRODUCTION

Glaucoma, the second leading cause of blindness in the world, is a group of optic neuropathy disorders that lead to loss of vision if left untreated. It is estimated that there will be approximately 80 million people worldwide affected by glaucoma by 2020.

In 2010, glaucoma affected more than 2.7 million Americans age 40 and older, which is approximately 2% of the population. Glaucoma is the third cause of blindness in New Zealand. According to the census of the Glaucoma New Zealand website, glaucoma is the leading cause of blindness in New Zealand and it is estimated that approximately 91,000 New Zealanders have the disease but are not aware of it.

Because of the rapid increase in aging populations, accurate diagnosis is critical for making treatment decisions to preserve vision and maintain quality of life. Stereoscopic disc photos provide an appropriate record of the optic nerve, independent of the specialized viewing instrument.

Stereoscopic disc photos remain one of the most widely used and accepted methods for documentation of the optic nerve head. However, due to its subjective nature, assessment of optic disc photographs for presence of glaucoma is labor-intensive and prone to interpretation errors. From a clinical perspective, many eye care specialists prefer to have access to more objective analyses for glaucoma diagnosis. Five rules for assessment of fundus stereo-photographs to identify glaucoma and monitor its progression over time have been described by Fingret et al.

Recent advances in artificial intelligence and a significant growth in available data have enhanced Identification of ocular disorders including glaucoma diagnosis. In particular, deep learning techniques can identify highly complex patterns to detect various ocular pathologies.

Identifying *glaucomatous optic neuropathy* (GON) based on ONH photographs is one of the standard methods used for glaucoma diagnosis. This process is labor-intensive and biased by reader variations. In this paper, we propose an automated technique based on deep learning and transfer learning that can differentiate between normal eyes and those with glaucoma using ONH photographs. We selected the regions of interest within the ONH photographs, namely regions which included the cup. In fact, the *cup-to-disc ratio* (CDR) is one *Convolutional neural networks* (CNNs) have been widely used for image segmentation and classification.

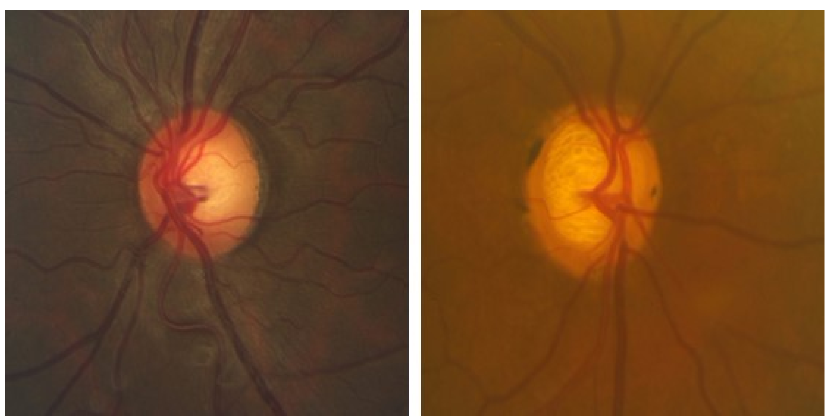

Figure 1: ONH Photographs from UCLA Dataset. Left: ONH Photographs from a Abnormal eye. Right: ONH Photographs from an Eye with Glaucoma.

Transfer learning is widely implemented in developing deep learning frameworks to address restrictions due to the limited number of input samples as well as computational resources for running deep learning techniques. Transfer learning employs the weights and parameters that were learned from previous large labeled datasets and applies them to the new task.

DATASETS

The Singapore Malay Eye Study's Online Retinal Fundus Image Dataset for Glaucoma Analysis and Research(ORIGA) database has 650 images (SiMES). The Singapore Eye Research Institute is in charge of SiMES (SERI).

Retinal fundus image is an important modality to document the health of the retina and is widely used to diagnose ocular diseases such as glaucoma, diabetic retinopathy and age-related macular degeneration. However, the enormous amount of retinal data obtained nowadays is mostly stored locally; and the valuable embedded clinical knowledge is not efficiently exploited. In this project we present an online depository, ORIGA(-light), which aims to share clinical ground truth retinal images with the public provide open access for researchers to benchmark their computer aided segmentation algorithms. In the UK, hospital eye services (HES) are the busiest outpatient service in the National Health System (NHS) and are responsible for 8.3% of all outpatient activity B. Glaucoma accounts for 25% of HES appointments. Individuals with, or at risk of, glaucoma are detected by community optometrists and referred to HES, 15%–20% of the new referrals will have glaucoma and around 50% will be discharged at the first visit, costing the NHS upwards of £75m/year..An in-house image segmentation and grading tool is developed to facilitate the construction of ORIGA(-light). A quantified objective benchmarking method is proposed, focusing on optic disc and cup segmentation and Cup-to-Disc Ratio (CDR). Currently, ORIGA(-light) contains 650 retinal images annotated by trained professionals from Singapore Eye Research Institute. A wide collection of image signs, critical for glaucoma diagnosis, are annotated. We will update the system continuously with more clinical ground-truth images. ORIGA(-light) is available for online access upon request.

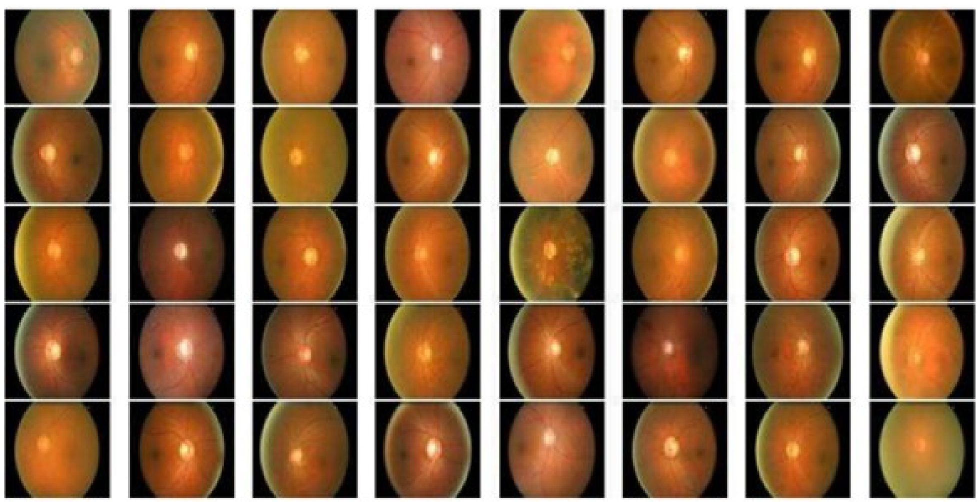

Figure 1.1: Data Set.

METHODOLOGY

The sample of the eye is roughly 2.3cm in diameter and is almost a spherical ball filled with some fluid captured from the patient for undergoing the test. An ophthalmoscopic camera is used to filter out undesired light reflected from the cornea of a patient's eye. The test image is sent to the controller unit for further processing. In the pre-processing stage, the test image then goes through various segmentation and filtering processes to enhance the image to increase the prediction accuracy. The test image is fed to the pretrained InceptionResNetV2 model to get the prediction metrics after passing through various mathematics-based pictorial manipulation layers. Then predictions are made to obtain a boolean binary value (i.e, either True or False) for a given set of features of a classification process as shown in Fig. 2. This helps in predicting the results. The Database used in this system is virtually located therefore the image and prediction results are then sent to the server database to visualize the results on the user interface. The predicted results will be generated and displayed in the web app interface.

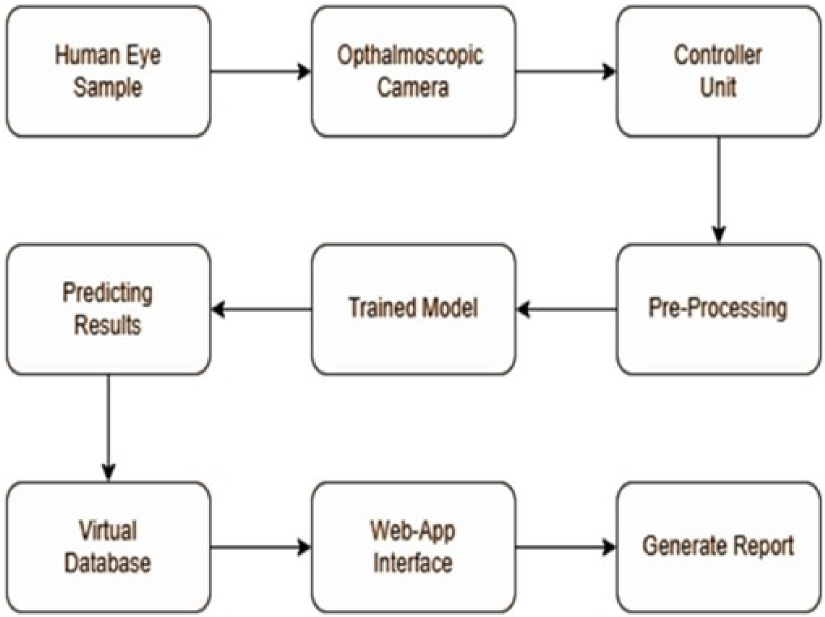

Figure 2: Methodology.

Inception ResNet-V2

An InceptionResNetV2 custom classifier is used to take fundus images and classify them into normal and positive glaucoma. The Inception-Resnet-V2 architecture with pretrained weights was employed for transfer learning. In the custom model, we froze the weights of the first 100 layers. The settings of the frozen layers are not changed by the trained network. To speed up network training and avoid dataset over fitting, several early layer weights might be frozen. The CNN model Inception-ResNet-v2 was trained using the Image Net dataset, which contains over a million images. The network has 164 layers and can categorize roughly 1000 item categories. As a result, the network model can learn complex attribute representations for a wide range of images. The Inception-Resnet block combines multiple-sized convolutional filters and residual connections.

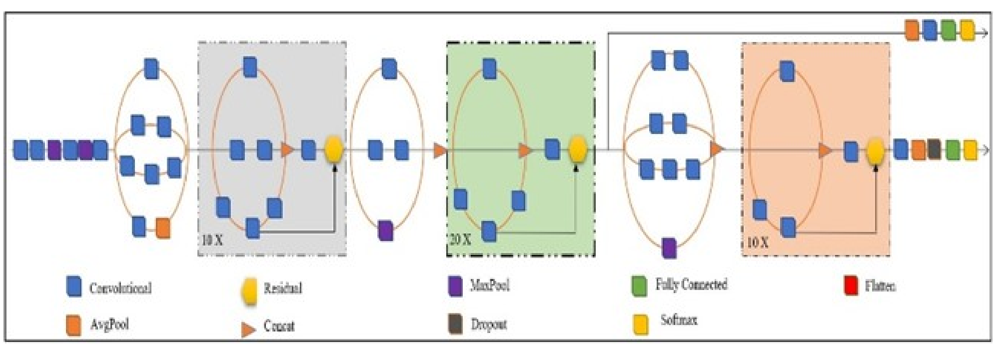

Figure 3: Inception-ResNet-V2 Architecture.

This was done in order to cut down on the amount of variables. As it progresses up to a neural network layer, the BN layer will make each mini-batch constellation map the same, preventing gradients from fading. It's a group of constellations that act as a training ground for any other constellation. We must additionally calculate **Jacobians** in the **back propagation process**. These are just partial derivations of the variables a and x's norms.

$$\frac{\delta Norm(a,\chi)}{\delta a} \text{ and } \frac{\delta Norm(a,\chi)}{\delta \chi} \quad \textbf{EQ 1.1}$$

Adam Optimizer is employed in the network to optimize the network parameter and minimize the loss. The method is highly efficient when dealing with huge situations with a lot of data or parameters. It's quick and doesn't take up a lot of memory.

$$\theta_x := \boldsymbol{\theta}_{x-1} - \boldsymbol{\alpha} \cdot \frac{\widehat{m_x}}{\sqrt{v_x + \varepsilon}} \quad \textbf{EQ 1.2}$$

Here $\alpha \epsilon R$ and $\theta, \widehat{m_x}$, $\hat{v}_x$, $\varepsilon \epsilon R$ for some n.

The following is the dropout equation for probability pi ($1 \leq i <= t$)

$$E_R = \frac{I}{2}(X - \sum_{i=I}^{t} \quad p_i \omega_i I_i)^2 + p_i(I - p_i)\omega_i^2 I_i^2 \alpha \quad \textbf{EQ 1.3}$$

The test image is fed to the pretrained InceptionResNetV2 model to get the prediction metrics after passing through various mathematics based pictorial manipulation layers. Predicting Results: The complete prediction metric is processed to obtain a boolean binary value (i.e, either True or False) for a given set of features of a classification process. The Inception-Resnet-V2 architecture with pretrained weights was employed for transfer learning The Database used in this system is virtually located therefore the image and prediction results are then sent to the server database to visualize the results on the user interface. The UI/UX part of the Web-App is creatively designed as per modern trends to increase use case of the utility. Based on the prediction metrics and feature metrics, a brief report about the test is generated which can also be viewed and downloaded by the user from the Web-App.

RESULTS AND EVALUATION CRITERIA

Using a Web-App, the suggested system may diagnose Glaucoma disease simply by taking live Ophthalmoscopic camera images. The web-app is powered by a well trained InceptionResNetV2 model.

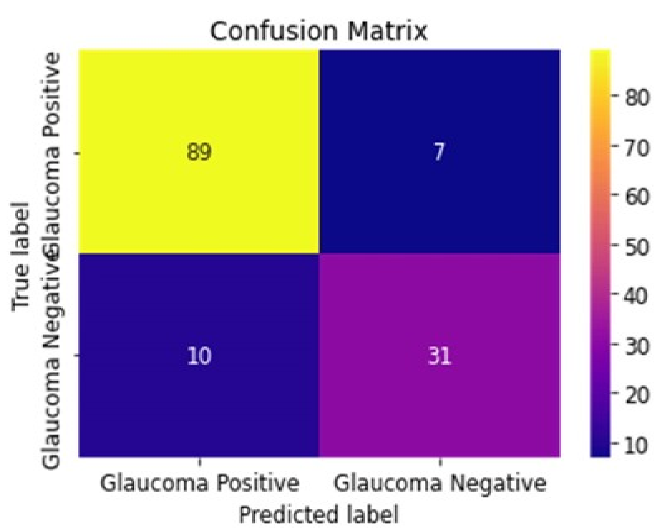

Figure 4: Confusion Matrix Plot Without Normalization.

The automatic detection of glaucoma by using a combination of image processing, artificial intelligence and computer vision can help to prevent and detect this disease. In this review article, we aim to present a comprehensive review about the various types of glaucoma, causes of glaucoma, the details about the possible treatment, details about the publicly available image benchmarks, performance metrics, and various approaches based on digital image processing, computer vision, and deep learning. Cones allow for color and central vision. The retina however consists of many layers, and photoreceptors only constitute a small part of these. One could make use of several retinal imaging techniques. Examples of such techniques are Colour Fundus Photography (CF), Fundus Auto fluorescence (FAF), Near-Infrared Reflectance (NIR) and Optical Coherence Tomography (OCT). CF, FAF and NIR are imaging techniques while OCT is a cross-sectional imaging technique. OCT allows for accurately measuring the thickness of the retina, something that is not possible using the other imaging techniques.

From the Fig. 4, The confusion matrix without normalization, shows the matrix with number of images classified in each case. Sum of all the images in each case is equal to the total number of images. Confusion matrix with normalization, shows the matrix with binary values (ratio of number of images predicted for each case to the total number of images) classified in each case.

$$\boldsymbol{Accuracy} = (\boldsymbol{TP} + \boldsymbol{TN}) / (\boldsymbol{P} + \boldsymbol{N})$$

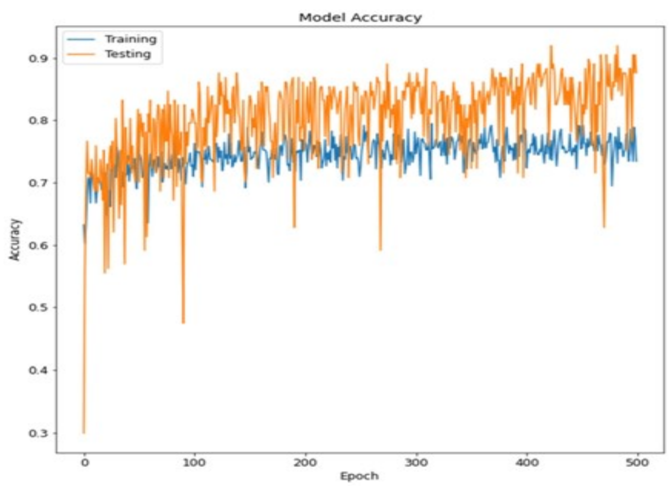

Figure 5

CONCLUSIONS

Glaucoma affects a vast number of people, and the burden of ophthalmologists has increased dramatically. The expert's fatigue may considerably enhance the rate of inaccuracy in these manual diagnostics and conclusions. From the above literature survey we have seen that the maximum accuracy was upto 87%, so our proposed system reached 88% accuracy and increased its effectiveness using InceptionResnetv2 which is newly developed transfer learning supportive models.

Developing a Web-App can be more helpful as it gives widespread access to the users to use it and get the earlier detections in the modern day world. To overcome this challenge, it goes without saying that a resolution which supports the systems is essential. The proposed arrangement employs a Web-app based on Python and Flask to forecast Glaucoma ophthalmoscopic camera images. As a result, anyone with access to the internet can obtain predictions in minutes.

As a result of their improved performance, ophthalmologists should be able to make better clinical decisions. This study demonstrates how a Web-App based on deep transfer learning can be used to diagnose Glaucoma in its early stages.

The results might not be precise when compared to those which are obtained in the physical world.

Figure 5: Model Accuracy

	Precision	Recall	f1-score	Support
Negative	0.90	0.93	0.91	96
Positive	0.82	0.76	0.78	41
Accuracy			0.88	137

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