Glaucoma Detection using Deep Convolutional Neural Network

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I. Introduction

Glaucoma is one of the most prevalent causes of blindness, with an estimated 80 million individuals affected by 2020.It is a chronic eye condition that causes vision loss by gradually damaging the optic nerve. Glaucoma is known as the "silent thief of sight" because symptoms do not appear until the illness is very advanced. Although glaucoma cannot be cured, it can be delayed with therapy. Early diagnosis of glaucoma using excellent pictures is critical.

One of the most common and widely used techniques for diagnosing glaucoma is the digital fundus image. Because DFIs may be obtained in a noninvasive way appropriate for large-scale screening, DFI has emerged as a favored modality for large-scale glaucoma screening. In a glaucoma screening program, an automated system determines whether or not a picture has any indications of glaucoma. Only pictures considered suspicious by the algorithm will be forwarded to ophthalmologists for additional review.

Glaucoma is diagnosed primarily by the intra-ocular pressure, and visual field loss tests, as well as a physical examination of the Optic Disc (OD) via ophthalmoscopy. The optic nerve is formed when ganglion cell axons depart the eye and form the optic nerve, which transmits vision information from photoreceptors to the brain. The OD may be split into two different zones in 2D images: a core bright zone known as the optic cup and a peripheral region known as the neuroretinal rim. The loss of optic nerve fibers causes a change in the structural appearance of the OD, namely the expansion of the cup area. Cupping is a term used to describe the narrowing of the neuroretinal rim.

Because enlargement of the cup with respect to OD is one of the main indications, several variables are examined and calculated to identify glaucoma, such as the vertical cup to disc ratio (CDR), disc diameter, ISNT rule, and parapapillary atrophy (PPA).

For completing this task there would be some challenges like Image Data pre-processing, identifying the best hyper parameter for the CNN Model etc.

II. Related Work

ARGALI, an automated glaucoma detection system, uses multiple approaches for segmenting the optic cup and disc from retinal pictures, which are then merged using a fusion network to estimate the cup to disc ratio (CDR), a key clinical indication of glaucoma. This article addresses the use of SVM as an alternate fusion approach in ARGALI and compares its performance in the CDR calculation to component methods and neural network (NN) fusion. The

findings demonstrate that SVM and NN give comparable gains over the component approaches, but SVM has higher consistency than NN, suggesting that SVM has the potential to be a viable choice in ARGALI [1].
The neuro-retinal optic cup-to-disc ratio can be used to diagnose glaucoma (CDR). When the optic disc region of interest (ROI) is correctly determined, it produces a smaller initial image that takes significantly less time to process than the whole image. The previous ROI localization approach in the ARGALI system was grid-based. Before examining the picture, the new algorithm does some preprocessing. This step substantially enhances the ROI detection's performance. The performance of the two techniques was compared using a set of 1564 retinal pictures from the Singapore Eye Research Centre. According to the results, the previous and new algorithms successfully recognize the ROI in 88 percent and 96 percent of the pictures, respectively [2].
In this paper The ARGALI system is used. The ARGALI system is made up of many stages. Because the optic disc constitutes such a tiny portion of the retinal picture, an area of interest is first identified using pixel intensity analysis. The optic disc is then segmented using a variational level-set method. Because the cup is intertwined with blood arteries and surrounding tissues, segmenting the optic cup is more difficult. The cup is extracted using a multi-modal technique comprised of several approaches. To provide a smoother shape, the removed cup and disc are fitted with an ellipse. A neural network has also been presented as a means of fusing the findings collected through the various modalities. The ARGALI system was evaluated using pictures gathered from patients at the Singapore Eye Research Institute and achieves an RMS error of 0.05 with a risk assessment accuracy of 95% [3].

III. Project Objective

The main objective of our project is detect glaucoma from images. For obtaining our objective we need to do some steps to complete the total process. These process are:

- Data acquisition
- Data pre-processing
- Model Training
- Classification
- Result analysis

We can see the whole process from the flow chart noted below:

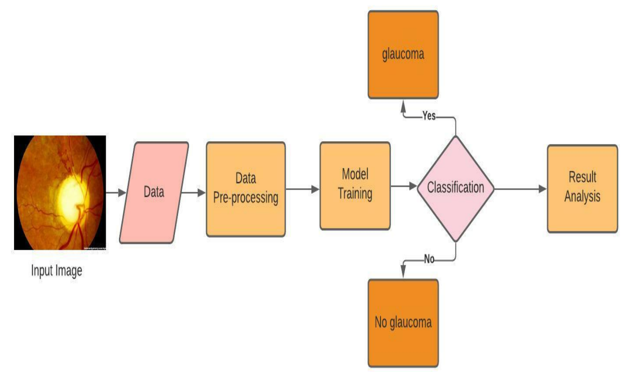

Figure 1: Overview of project workflow

IV. Methodology

A. Structure of Model:

We created a deep learning system for capturing discriminative features that better define glaucoma-related hidden patterns. The DL structure used consists of six layers: four convolutional layers and two fully-connected layers that infer a hierarchical representation
of pictures to differentiate between glaucoma and non-glaucoma patterns for diagnostic judgments.
Convolutional layers are commonly used to train tiny feature detectors based on

randomly sampled patches from an image. By converging the feature detector and the picture at that position, a feature in the image at that place may be computed.

In the proposed deep learning architecture, response-normalization layers come after the first and second convolutional layers. The These saturating nonlinearities, on the other hand, are significantly slower than the non-saturating nonlinearity f(x) = max (0,x). Rectified Linear Units are neurons having this nonlinearity (ReLUs).

In CNNs, pooling layers summaries the statistics of a feature over an area of the picture. A pooling layer is made up of a grid of pooling units spaced p pixels apart, each summarizing a neighborhood of size s*s centered at the pooling unit's position. We get traditional local pooling when p = s. When p<s, we have overlapping pooling, which might assist with overfilling. Max-pooling layers come after both the response-normalization layers and the convolutional layer in our learning architecture as shown in fig 2 and 3.

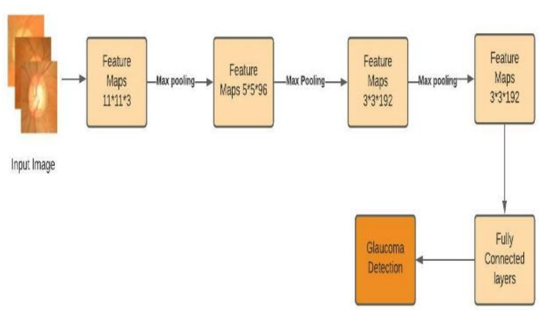

Figure 2: CNN Model

typical approach to compute a neuron's output in a neural network is to use f(x) = tanh(x) (x is the input).

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 255, 255, 32)	416
activation (Activation)	(None, 255, 255, 32)	0
max_pooling2d (MaxPooling2D)	(None, 127, 127, 32)	0
conv2d_1 (Conv2D)	(None, 126, 126, 32)	4128
activation_1 (Activation)	(None, 126, 126, 32)	0
max_pooling2d_1 (MaxPooling2	(None, 63, 63, 32)	0
conv2d_2 (Conv2D)	(None, 62, 62, 64)	8256
activation_2 (Activation)	(None, 62, 62, 64)	0
max_pooling2d_2 (MaxPooling2	(None, 31, 31, 64)	0
conv2d_3 (Conv2D)	(None, 30, 30, 64)	16448
activation_3 (Activation)	(None, 30, 30, 64)	0
max_pooling2d_3 (MaxPooling2	(None, 15, 15, 64)	0
flatten (Flatten)	(None, 14400)	0
dense (Dense)	(None, 64)	921664
activation_4 (Activation)	(None, 64)	0
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 1)	65
activation_5 (Activation)	(None, 1)	0

Total params: 950,977
Trainable params: 950,977
Non-trainable params: 0

Figure 3: CNN Model Structure

B. Classification With CNN

For glaucoma prediction, the output of the last two fully connected layers is input into a sigmoid activation function. Our suggested deep learning architecture, we employ dropout in the two fully-connected layers. Dropout is achieved by changing the output of each hidden neuron to zero with a probability of 0.5. We employ the ROI picture as the input to the proposed deep Convolutional Neural Network (CNN), which provides a smaller starting image that takes considerably less time to analyze than segmenting the disc and cup.

We employed response-normalization layers and overlapping-pooling layers to reduce overfitting. Dropout is also used in the proposed DL architecture to improve performance even more.

V. **Experiments:**

A. **Dataset**: In this project we used ORIGA Dataset [4] for glaucoma detection. ORIGA Data set contains Image around 610 and The ORIGA dataset with clinical glaucoma diagnoses, is comprised of 168 glaucoma and 482 normal fundus images. We split the dataset into 2 part 535 image for Test Set and 75 Image for Test set. We can see the whole data distribution from table below:

Dataset Name	Total Image	Train	Test
ORIGA Dataset	610	535	75

Table 1: Data distribution

B. Evaluation: we are going to evaluate our model with some common metric. These are:

- For Accuracy we used a formula:

$$accuracy = \frac{True\ Positive + True\ negative}{True\ Positive + True\ negative + False\ \ positive + False\ Negat}$$

- For Precision we used This formula:

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

- For Recall we used This formula:

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

- For F1-score we used This formula:

$$F1 - score = 2x\frac{Precisionx\ Recall}{Precision + Recall}$$

C. Results: After Completing The training and testing part we get classification results. The overall result of our model in this dataset is given below:

Dataset Name	Class	Epoch	Precision	Recall	F1-score
ORIGA Dataset	0	100	0.50	1.00	0.67
	1		0.50	0.00	0.00

Table 2: Result Overview

And we also get the epoch vs loss and epoch vs accuracy graph. Our model was able to reach the accuracy of 83.52%. These 2 graphs are noted below:

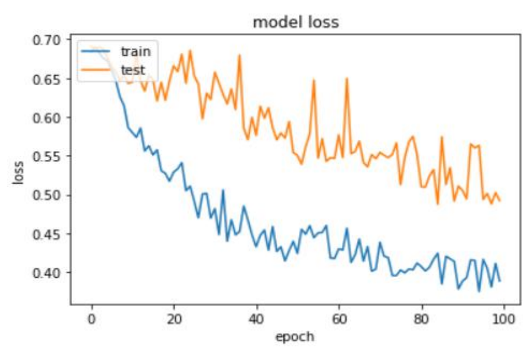

Fig 4: Epoch vs loss Graph

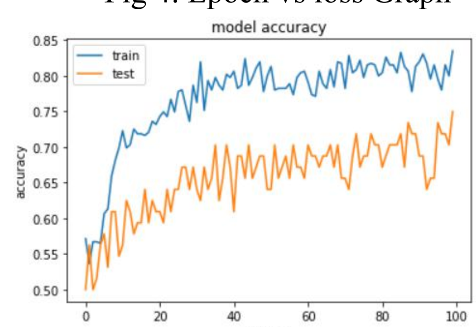

Fig 5: Epoch vs Accuracy Graph

From this two figure 4 and 5 we can see with the increment of epoch number the model gets better accuracy and loss is also decreased.

VI. Conclusion And future Work:

We offer a DL framework for glaucoma in this study. detection based on deep CNN, capable of capturing the distinguishing characteristics that better identify the hidden Glaucoma-related patterns The DL structure that was used consists of six layers: four convolutional layers and two fully-convolutional layers layers that are linked To alleviate the overfitting issue, we Implement response-normalization layers and overlapping-pooling layers. In future we would like to apply Transfer learning and Deep Learning based object detection models like YOLO, SSD etc for Glaucoma detection.

References:

[1] Wong, D.W.K., Lim, J.H., Tan, N.M., Zhang, Z., Lu, S., Li, H., Teo, M., Chan, K., Wong, T.Y.: Intelligent Fusion of Cup-to-Disc Ratio Determination Methods for Glaucoma Detection in ARGALI. In: Int. Conf. Engin. in Med. and Biol. Soc., pp. 5777–5780 (2009)

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