Optic Cup to Disc Ratio Calculation using Deep Convolutional Network

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Abstract: In this work, we propose a deep learning based Glaucoma detection method using a retinal fundus image. Based on the ratio of the optic cup to disc (CDR) we predict the severity of pathological Glaucoma. The proposed deep learning based method detects the exact location of the optic nerve head and the optic cup to predict the CDR. This approach allows us to compute the CDR robustly irrespective of the given retinal image quality. We evaluate our model on expert ophthalmologists annotated dataset.

Introduction: Glaucoma is a leading cause of blindness for people over 60 years old. But blindness from glaucoma can often be prevented with early treatment. Glaucoma is a disease that damages the eye's optic nerve. It usually happens when fluid builds up in the front part of the eye. That extra fluid increases the pressure in the eye, damaging the optic nerve.
Glaucoma can be detected using a retinal fundus image at the early stage, people with this disease tend to have a greater CDR. A cup to disc ratio greater than 0.6 [1] in the scale of 0 to 1 is generally considered to be suspicious for glaucoma. Fig 1 shows some cases of Glaucoma visible on the retinal fundus images.
Early detection of Glaucoma is necessary for successful diagnosis. In this work, we have developed deep learning based robust and accurate CDR calculation method. Based on CDR value, the severity of Glaucoma can be predicted.

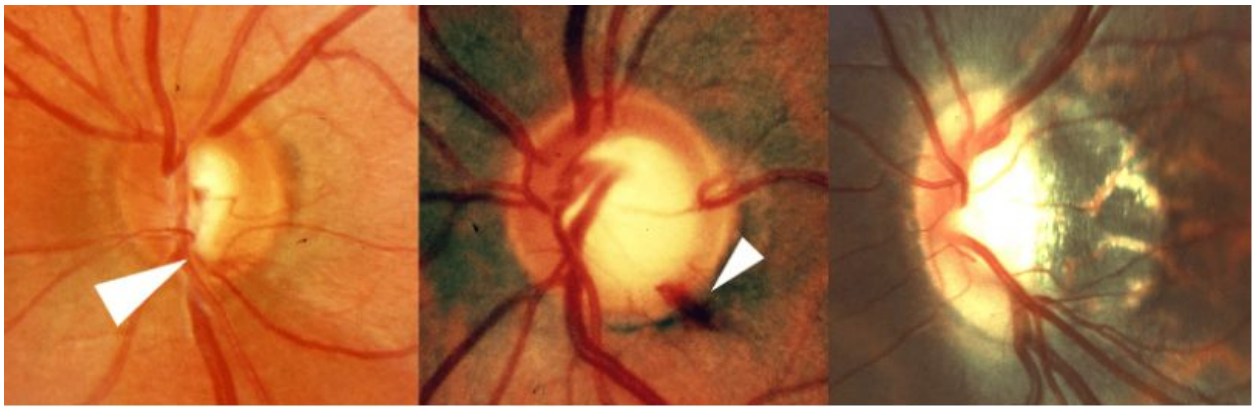

Fig 1: Left: cup extends abnormally to the inferior rim of nerve head (arrowhead); Middle: bleeding on the inferior disc rim, seen as a flame-shaped red area (arrowhead); Right: disc with an unusual shape and larger than normal cup/disc ratio. [2]

Dataset: For training and evaluating the model we have used a dataset developed at Artelus. It has around 5000 training images and 1000 validation images.

Methods: Deep learning based supervised methods [3] achieved state-of-the-art performance in tasks related to computer vision, natural language processing, speech processing, drug discovery, etc. Convolutional operations are very efficient in harvesting meaningful discriminative information from input data. For medical data, it is important to identify minute details to make the correct prediction.
Fig 2 depicts the proposed CNN architecture of our CDR calculation network. Image regions with high objectness scores are feed into the classifier to calculate the width of the optic disc and the optic cup.

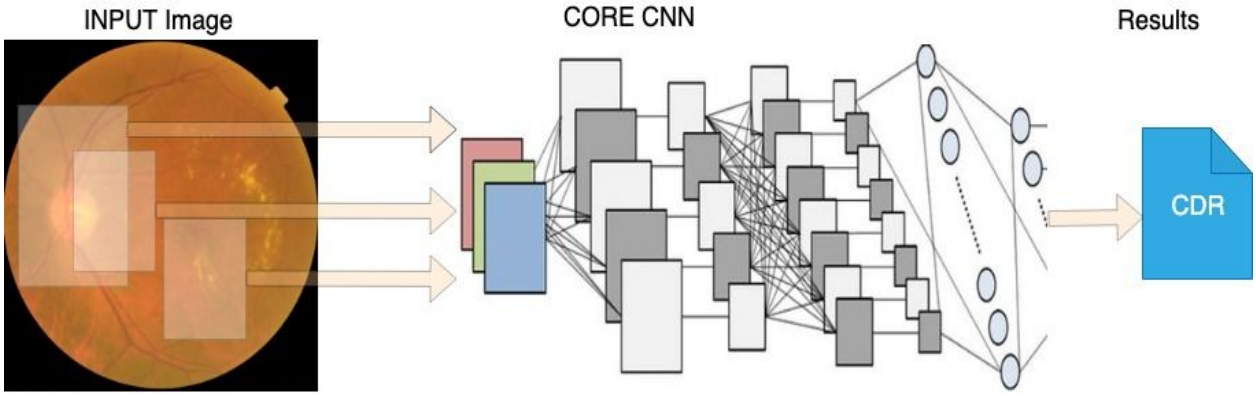

Fig 2: A depiction of our proposed CNN architecture.

We have used 80 layers deep convolutional deep networks to detect the optic disc and the optic cup from the input retinal fundus image. It has around 15M training parameters. Network parameters are optimized using Adam optimizer. Extensive data augmentation was used to improve the generalization capacity of the network.

Training: We have used our Tefla AI framework to build and train the model. Tefla is very efficient and fast deep learning platform that enables faster and easier model prototyping.
All the experiments were conducted using a GPU server with NVIDIA Titan X cards. For end-to-end training, it takes around 15 hours for completion of the experiment.

Results: We have validated the results on the internal test set (ARTFRGT001). ARTFRGXT001 details can be found in Appendix A-1. Fig 3-5 shows the deep learning based system predicted CDR on three sample images. Fig 3 shows an image unusual cup shape and high CDR of 0.68, predicting the possibility of mild glaucoma. Fig 4 and Fig 5 show images with low CDR predicting no sign of Glaucoma.
We have overserved that the method can calculate CDR even from low-quality input fundus image. Input fundus image is expected to have the optic disc in the field of view.

Grading: We grade Glaucoma on a scale of 0 to 4, according to the following scale:
Normal (0): CDR < 0.6, Mild (1): 0.6 <= CDR < 0.7, Moderate (2): 0.7 <= CDR < 0.8
Severe (3): 0.8 <= CDR < 0.9, Proliferative (4): 0.9 <= CDR < 1.0

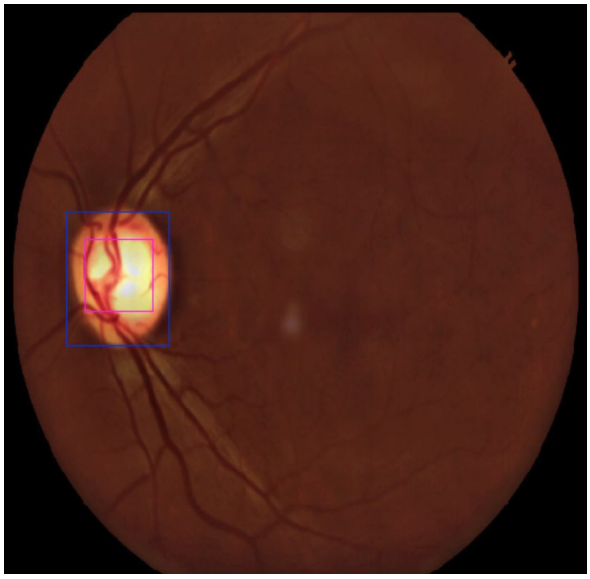

Fig 3: CDR: 0.68

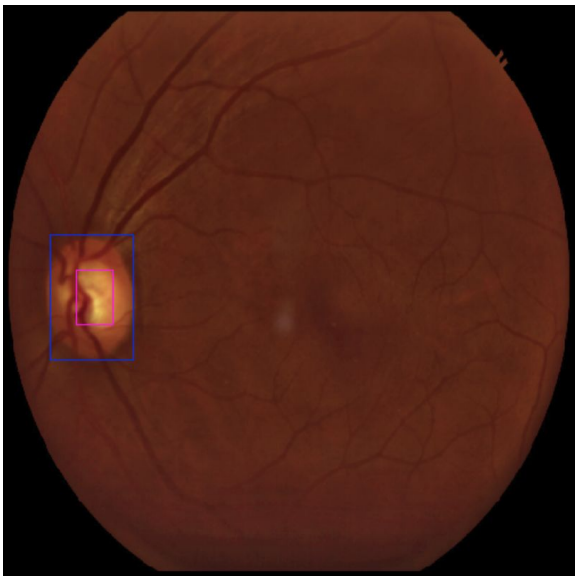

Fig 4: CDR=0.39

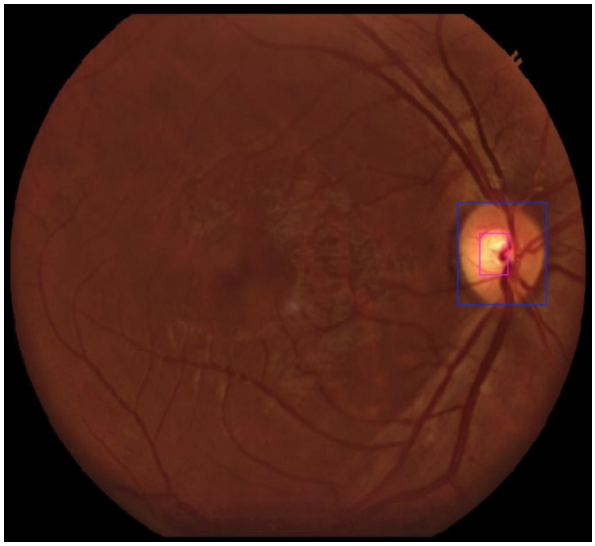

Fig 5: CDR=0.35

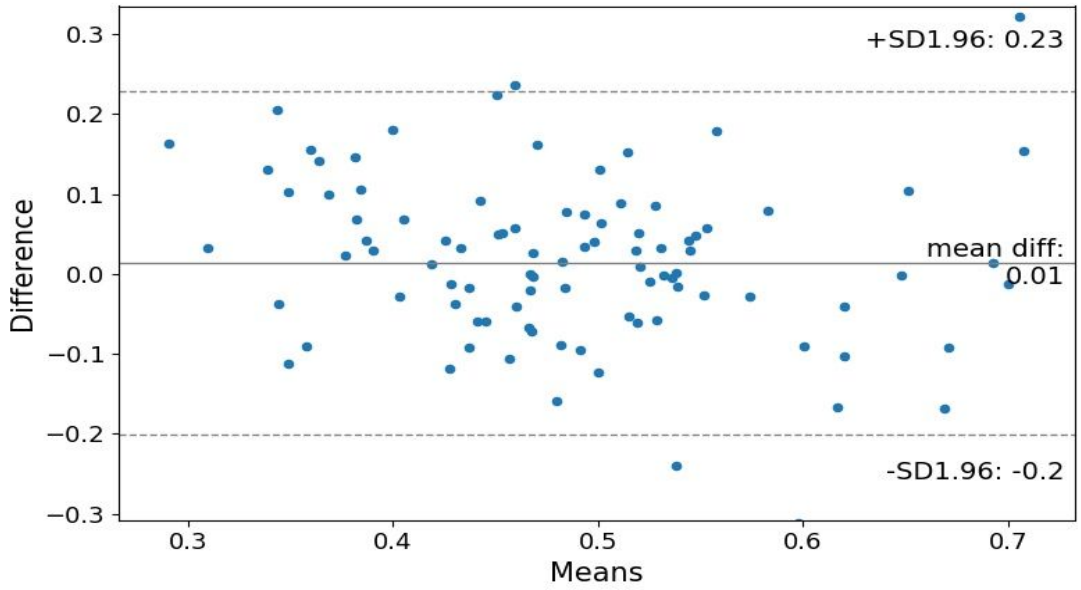

Fig 6: Bland-Altman plot for horizontal cup-to-disc ratio (CDR_X) demonstrating agreement between a retina specialist and ARTFRGX model. The x-axis indicates the average CDR_X of a retina specialist and ARTFRGX; y-axis indicates the difference between CDR_X of and retina specialist and ARTFRGX.

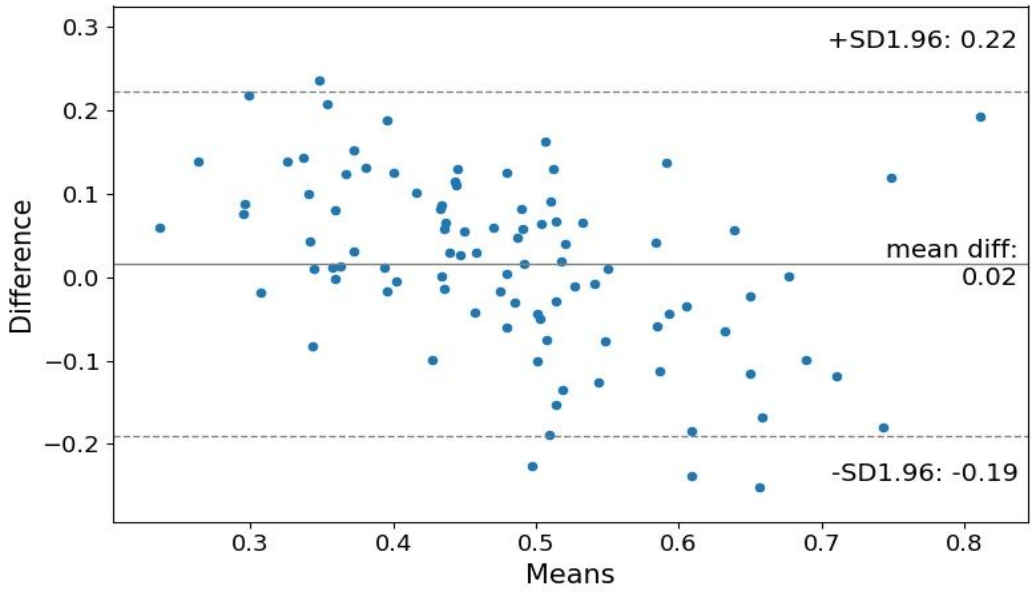

Fig 7: Bland-Altman plot for vertical cup-to-disc ratio (CDR_Y) demonstrating agreement between a retina specialist and ARTFRGX model. The x-axis indicates the average CDR_Y of a retina specialist and ARTFRGX; y-axis indicates the difference between CDR_Y of and retina specialist and ARTFRGX; y-axis indicates the difference between CDR_Y of and retina specialist and ARTFRGX.

Fig 6 and Fig 7 demonstrates the results using bland-altman plot. We can infer that there's no consistent bias of the ARTFRGX model versus the retina specialist as the test data cases are evenly distributed.

Table 1: MAE and RMSE values for CDR_X and CDR_Y on ARTFRGT001 dataset. Lower metrics values mean better model.

Metrics/Params	MAE ↓	RMSE ↓
CDR_X	0.08	0.01
CDR_Y	0.09	0.01

Table 1 shows the results obtained on the test set, we have evaluated using mean-absolute-error (MAE) and root-mean-squared-error (RMSE). MAE and RMSE values are computed against annotation by a retina specialist. As we can infer that the AI model was able to predict CDR values with very good RMSE and MAE values.

Conclusion: We have successfully applied a deep convolutional network for CDR prediction. The proposed method is under validation by experienced ophthalmologists in our on-going internal study. We aim to release the product for the mass market to help ophthalmologists to take a faster and accurate decision.

References:

1. https://www.glaucoma.org/glaucoma/optic-nerve-cupping.php
2. https://www.hopkinsmedicine.org/wilmer/services/glaucoma/book/ch06s03.html
3. Haloi, M. (2015). Improved microaneurysm detection using deep neural networks. *arXiv preprint arXiv:1505.04424*.

Appendix A:

1. ARTFRGT001 Test dataset details

Table 2: ARTFRGT001 dataset cases details.

Characteristic	Values
Mean Age	53
Male	46.2 %
Female	53.8 %
Chronic simple glaucoma	23.1 %
Eye hypertension	76.9 %