Glaucoma Detection using Deep Learning and Image Processing

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in partial fulfilment of the requirements for paper

III.6.3:Biochemical and Molecular Perspective

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Contents

1.Introduction

Glaucoma is one of the major leading causes of blindness among eye diseases, predicted to affect around 80 million people by 2020. Unlike other eye diseases such as cataracts and myopia, vision loss from glaucoma cannot be reversed. Early screening is thus essential for early treatment to preserve vision and maintain life quality. However, many glaucoma patients are not aware of their condition. That is why glaucoma is also called the "silent theft of sight". Clinically, there are three examinations practised to screen glaucoma: intraocular pressure (IOP) measurement, function-based visual field test, and optic nerve head (ONH) assessment. IOP is an important risk factor but not specific enough to be an effective detection tool for a great number of glaucoma patients with normal tension. One popular ONH assessment method is based on the measurement of clinical parameters, such as the vertical cup to disc ratio (CDR), rim to disc area ratio, and disc diameter. Among them, CDR is well accepted and commonly used by clinicians. As shown in the top row of Fig. 1, the CDR is calculated by the ratio of vertical cup diameter (VCD) to vertical disc diameter (VDD). In general, a larger CDR suggests a higher risk of glaucoma and vice versa.

2. Disease Description

Glaucoma is a disease of the eye in which fluid pressure within the eye rises; if left untreated, the patient may lose vision and even become blind.

Glaucoma is relatively common, especially in older adults and can cause damage to the optic nerve if left untreated.

With all types of glaucoma, the nerve connecting the eye to the brain is damaged, usually due to high eye pressure.

The most common type of glaucoma (open-angle glaucoma) often has no symptoms other than slow vision loss. Angle-closure glaucoma, although rare, is a medical emergency and its symptoms include eye pain with nausea and sudden visual disturbance.

Treatment includes eye drops, medication and surgery.

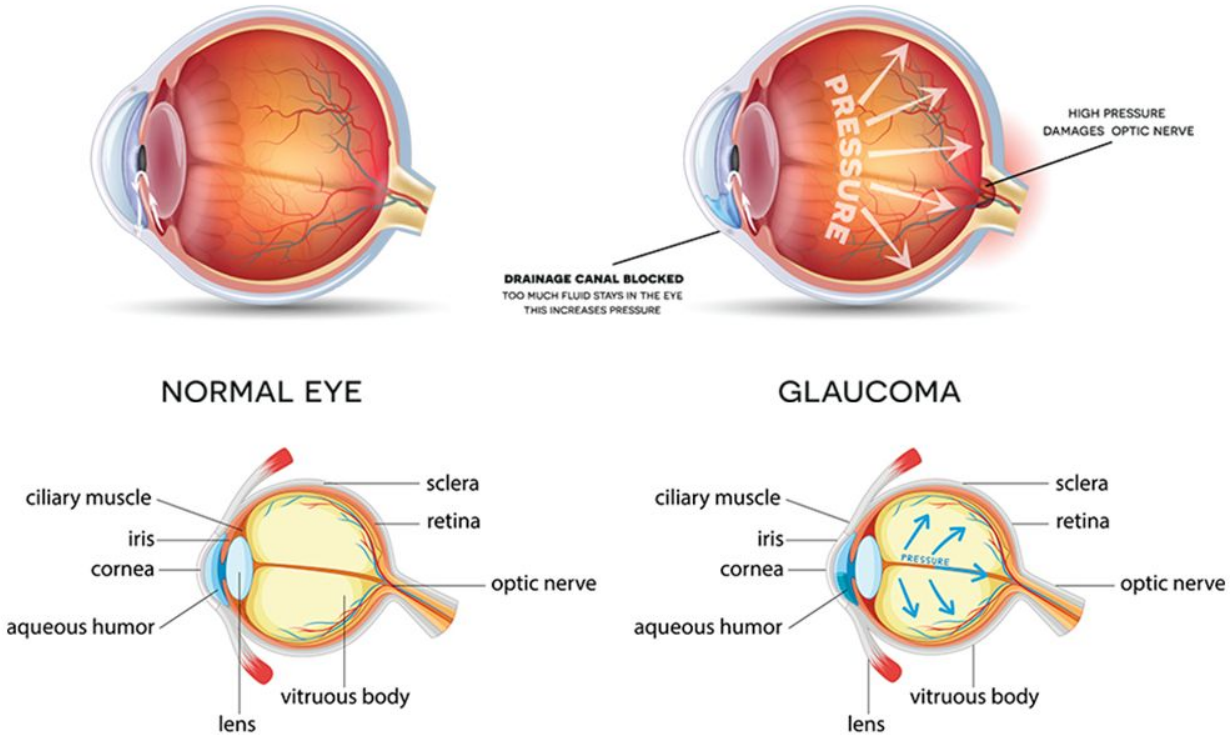


Fig. Development of Glaucoma

3.Dataset Description

The dataset used in the current project is RIGA Dataset.

The dataset includes 3 different files:

1) MESSIDOR dataset file contains 460 original images and 460 images for every single ophthalmologist manual marking in a total of 3220 images for the entire file.

2) Bin Rushed Ophthalmic centre file and contains 195 original images and 195 images for every single ophthalmologist manual marking in a total of 1365 images for the entire file.

3) Magrabi Eye centre file and contains 95 original images and 95 images for every single ophthalmologist manual marking in a total of 665 images for the entire file. The total of all the dataset images is 750 original images and 4500 manual marked images. The images are saved in JPG and TIFF format.

I have preferred this dataset over other available datasets like DRION which contains only a few number of images (90).
Where as the ORIGA dataset was released to public due to clinical policies. To access that database we needed to request access.

4. Concepts Involved

4.1 U-Net

The U-net architecture is synonymous with an encoder-decoder architecture. Essentially, it is a deep-learning framework based on FCNs; it comprises two parts:
1. A contracting path similar to an encoder, to capture context via a compact feature map.
2. A symmetric expanding path similar to a decoder, which allows precise localisation. This step is done to retain boundary information (spatial information) despite downsampling and max-pooling performed in the encoder stage.

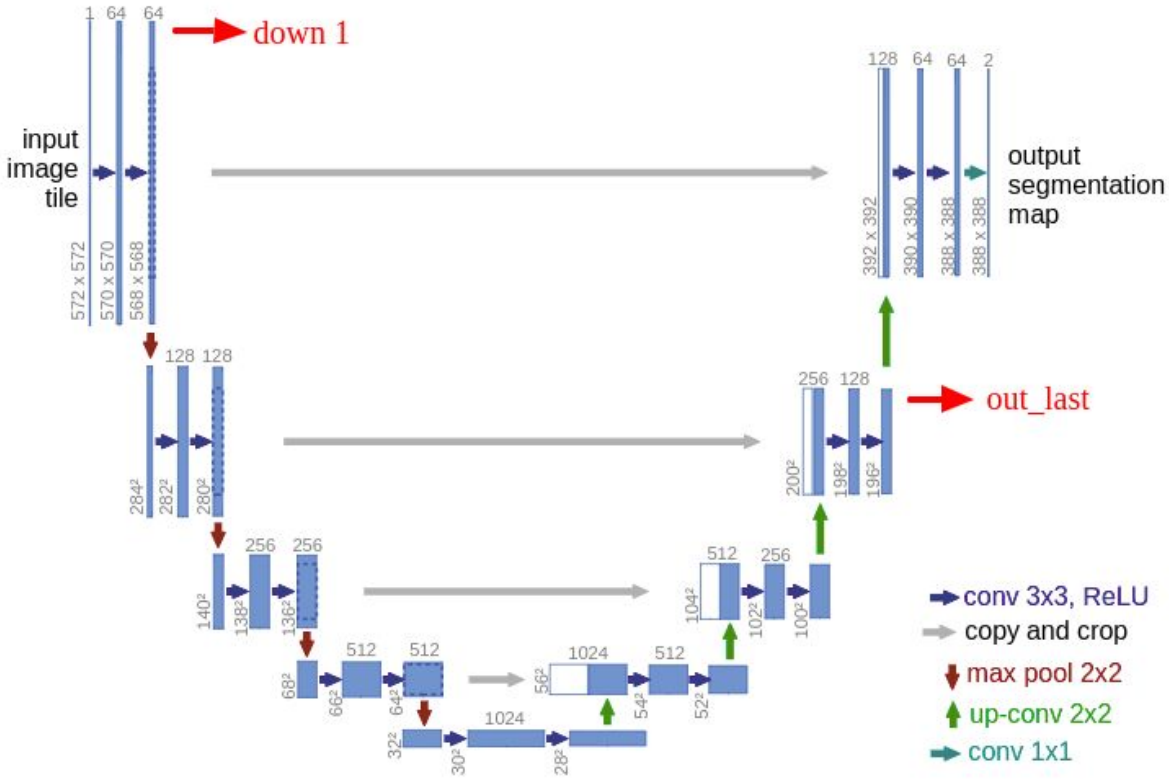


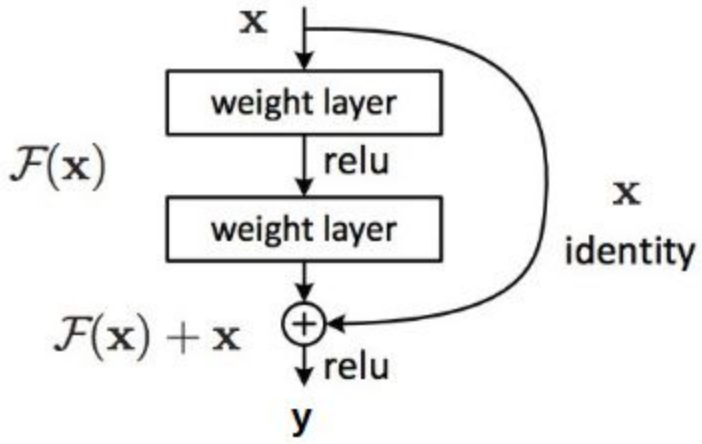
Fig 1. Architecture of U-Net

4.2 Resnet

ResNet is a short name for Residual Network. As the name of the network indicates, the new terminology that this network introduces is residual learning.

Deep convolutional neural networks have led to a series of breakthroughs for image classification. Many other visual recognition tasks have also greatly benefited from very deep models. So, over the years there is a trend to go more deeper, to solve more complex tasks and to also increase /improve the classification/recognition accuracy. But, as we go deeper; the training of neural network becomes difficult and also the accuracy starts saturating and then degrades also. Residual Learning tries to solve both these problems.

In general, in a deep convolutional neural network, several layers are stacked and are trained to the task at hand. The network learns several low/mid/high level features at the end of its layers. In residual learning, instead of trying to learn some features, we try to learn some residual. Residual can be simply understood as subtraction of feature learned from input of that layer. ResNet does this using shortcut connection (directly connecting input of nth layer to some (n+x)th layer. It has proved that training this form of networks is easier than training simple deep convolutional neural networks and also the problem of degrading accuracy is resolved.



$$y = x + F(x)$$

$$\frac{\delta E}{\delta x} = \frac{\delta E}{\delta y} * \frac{\delta y}{\delta x} = \frac{\delta E}{\delta y} * (1 + F'(x))$$

$$= \frac{\delta E}{\delta y} + \frac{\delta E}{\delta y} * F'(x)$$

Fig. 2 Calculating Gradient in ResNet

5. Methodology

The following Architecture of the proposed DENet, which contains four streams: global image stream produces the result based on the global fundus image; the segmentation guided network localizes the optic disc region and generates a detection output embedded the disc-segmentation representation; disc region stream works on disc region cropped by disc segmentation map from segmentation-guided network; disc polar stream transfers the disc region image into the polar coordinate system. The combination of these four streams is fused as the final glaucoma screening result.

Using the unmarked images, a neural network can be designed to predict the Optic Disk and Peripheral Cup using back propagation since ophthalmologist marked images are already present.

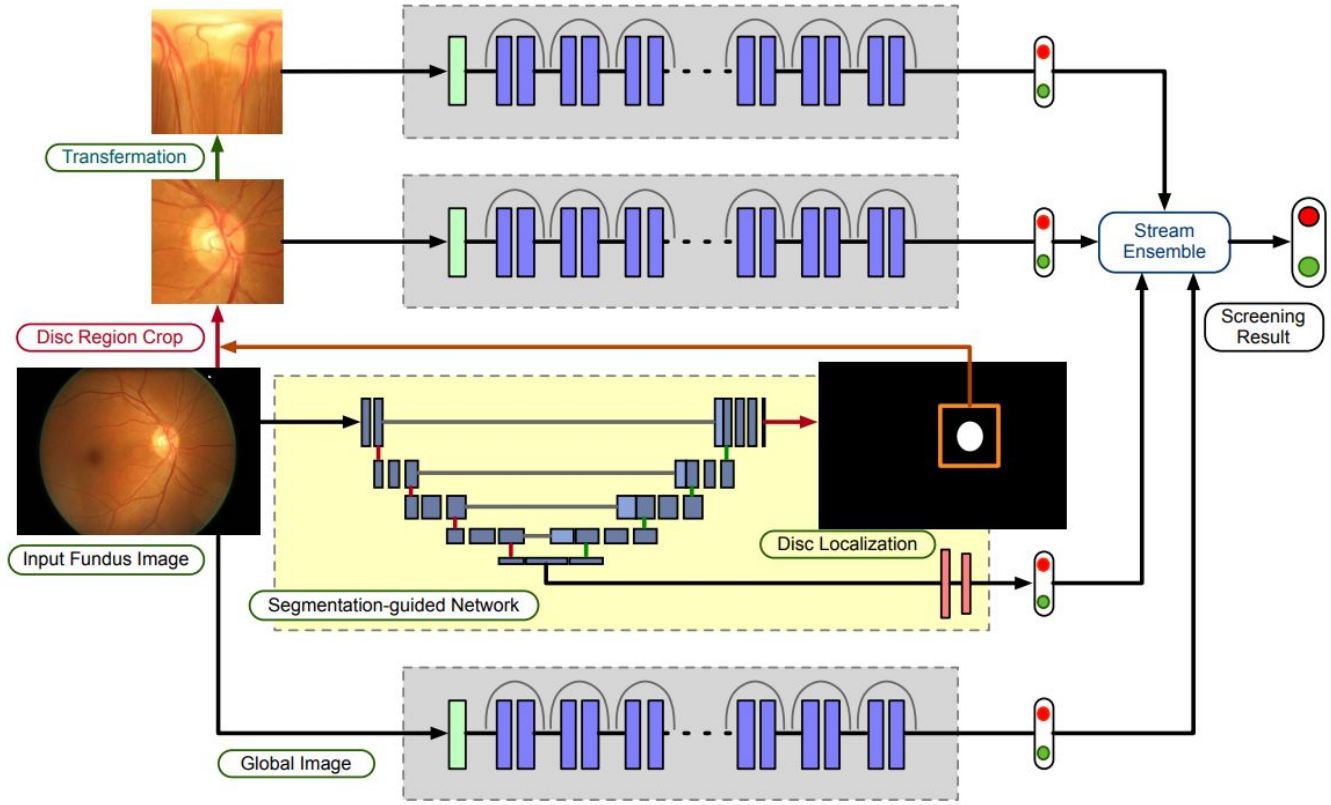


Fig 3. Algorithm used

Using the unmarked images, a neural network can be designed to predict the Optic Disk and Peripheral Cup using back propagation since ophthalmologist marked images are already present.

On completion of the training, the output images. Using image processing the HDCR and VDCR will be calculated.

To increase the efficiency of the algorithm an automation pipeline for the reduction of the image size is required. The new image shall only have the required features like the optic disc and the peripheral cup. This process will not be fully automated and requires human intervention.

The accuracy of optic disc region cropping disturbs the detection performance. The second level in our network is based on the local optic disc region, which is cropped based on the previous segmentation-guided network. The local disc region preserves more detailed information with higher resolution and it is benefited to learn a fine representation.

6. Results

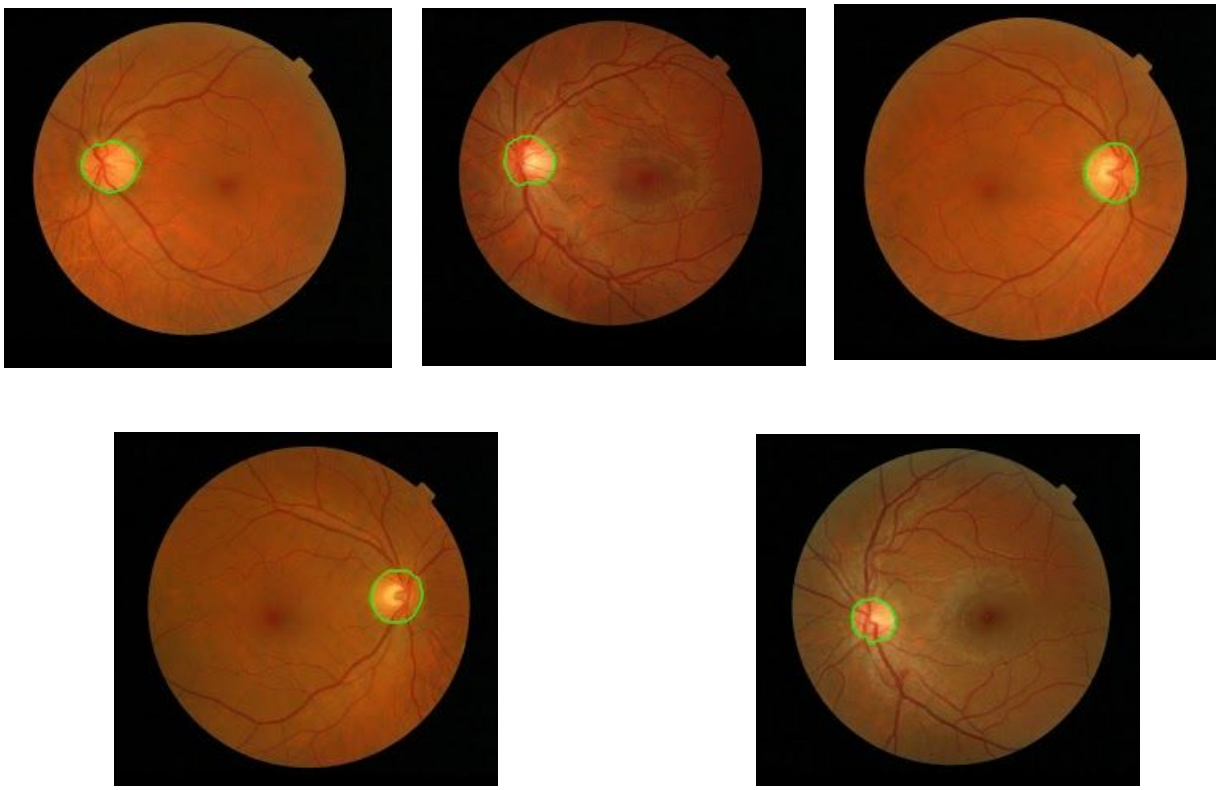


Fig. Final Output from the U-Net model detecting Optic Centre of the fundus image

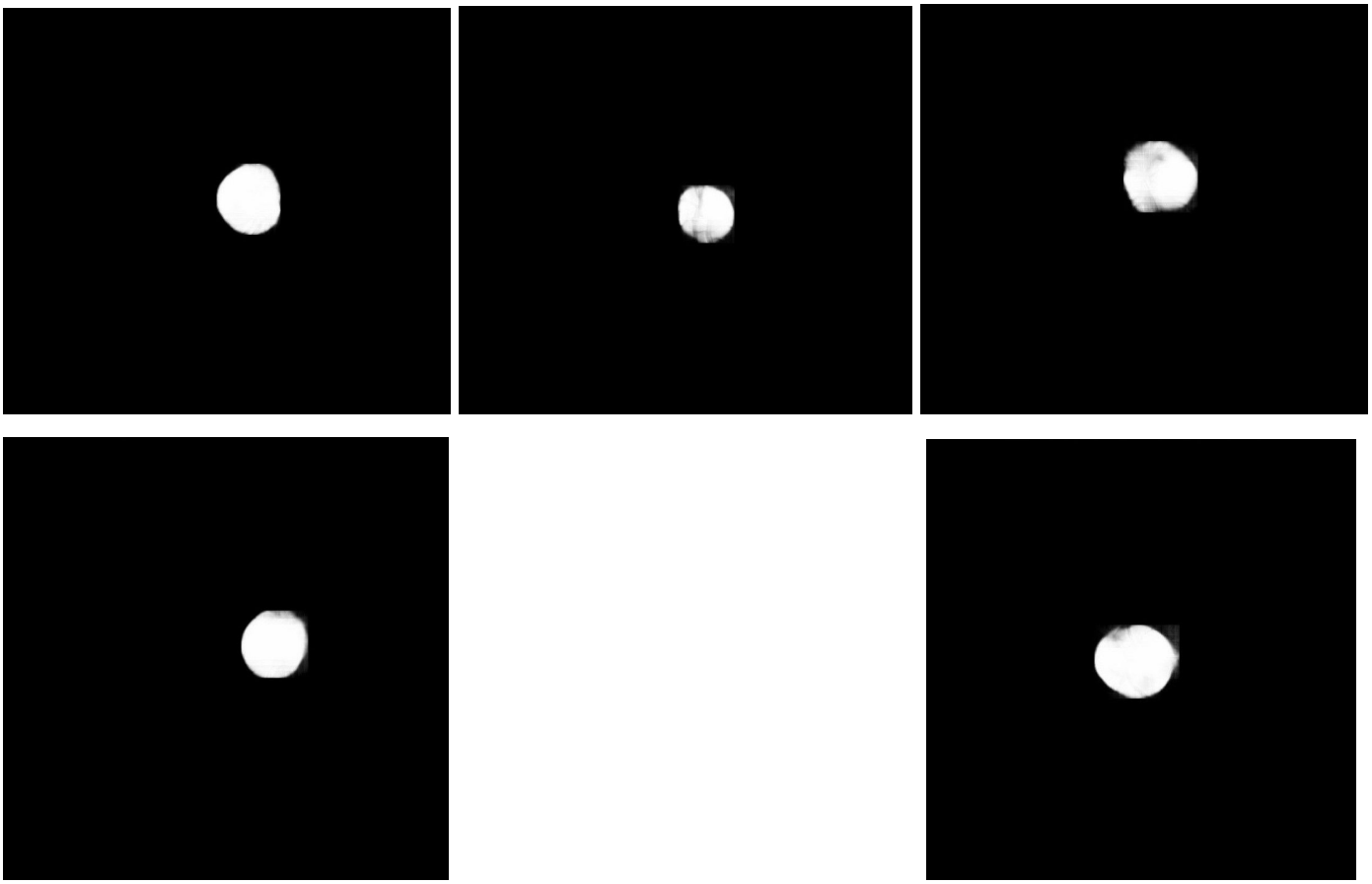


Fig. Masked Layers from U-Net Model for the detected Optic Centre

Fig. The segmentation done by the model.

FileName	Glaucoma Risk
V0001.jpg	0.28218
V0002.jpg	0.34816
V0003.jpg	0.027847
V0004.jpg	0.28081
V0005.jpg	0.28086
V0006.jpg	0.77814
V0007.jpg	0.23869
V0008.jpg	0.35365
V0009.jpg	0.28825
V0010.jpg	0.24779
V0011.jpg	0.018874
V0012.jpg	0.22376
V0013.jpg	0.23201
V0014.jpg	0.3038
V0015.jpg	0.24816
V0016.jpg	0.24682
V0017.jpg	0.37032
V0018.jpg	0.39568
V0019.jpg	0.24506
V0020.jpg	0.6983
V0021.jpg	0.28732

V0022.jpg	0.23451
V0023.jpg	0.2409
V0024.jpg	0.29467
V0025.jpg	0.18338

The above table contains the filename and the risk of the patient to confer to Glaucoma.

8. References

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