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IDENTIFICATION OF GLAUCOMA IN HUMAN FUNDUS IMAGES USING MULTI LEVEL DEEP CONVOLUTIONAL NEURAL NETWORK

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Abstract Retinal image analysis is an emerging research field in ophthalmological diseases. One of the leading ophthalmological diseases is glaucoma. Glaucoma is the leading cause for blindness. It affects the optic nerve of our eye. Due to its complexity and silent nature, early detection of this disease makes it hard to detect .In this article, we introduced convolutional neural networks in the deep learning field for the detection of glaucoma. Firstly, the fundus image of both healthy image and glaucoma image are collected with good lighting conditions,Then the CDR value for the image is obtained.Based on the CDR values obtained the result will be generated.

Keywords: CNN model, Glaucoma Detection, Image Segmentation, Cup Disk Ratio, Classification .

I. Introduction

Glaucoma is a second largest eye disease, causes blindness. Optic nerve connect to brain, help to scan image from eye .Glaucoma damages the optic nerve. Regular eye checkup only precautionary measure to avoid glaucoma. Glaucoma occur due to intraocular pressure more fluid produced on eye, leading to blockage on eye's channel. Glaucoma cannot be cured but it can be controlled. Glaucoma is an eye disorder in which the optic nerve is damaged due to increase in intraocular pressure with in the eye. Glaucoma is one of the leading causes of irreversible blindness in the world. It leads to deterioration in vision and quality of life if it is not cured early. The following figure illustrates us, how danger it is.

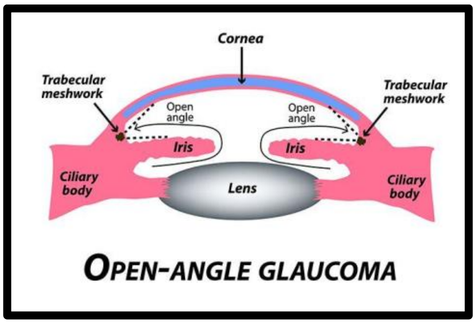
Types of Glaucoma

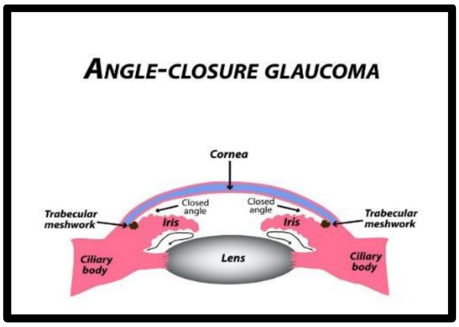
Open angle glaucoma

Open-angle glaucoma is the most common form of the disease. The drainage angle formed by the cornea and iris remains open, but the trabecular meshwork is partially blocked. This causes pressure in the eye to gradually increase. This pressure damages the optic nerve. It happens so slowly that you may lose vision before you're even aware of a problem.

Closed angle glaucoma

Closed-angle glaucoma occurs when the iris bulges forward to narrow or block the drainage angle formed by the cornea and iris. As a result, fluid can't circulate through the eye and pressure increases. It develops quickly. Some people have narrow drainage angles, putting them at increased risk of angle-closure glaucoma. It is also called angle closure glaucoma.

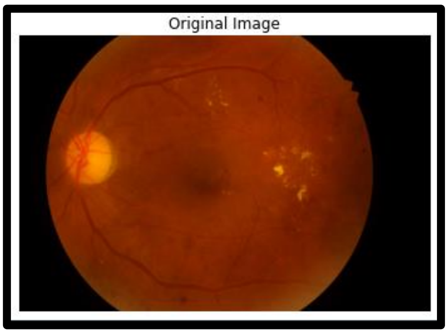




METHODOLOGY

Input Image

The input image is taken from dataset repository. The Glaucomatous fundus images and normal images are collected and stored in the dataset repository. The input dataset is in the format **'.png, '.jpg**. The input image by using the **imread ()** function. We have used the **tkinter** file dialogue box for selecting the input image.



Preprocessing

After selecting the input image we have to resize the image and convert the image into grayscale. To resize an image, we use **resize ()** method, passing in a two-integer tuple argument representing the width and height of the resized image. The function doesn't modify the given image; it instead returns another Image with the new dimensions. Then Converts the Image to Grayscale in Python Using the Conversion Formula and the matplotlib Library. We can also convert an image to grayscale using the standard RGB to grayscale conversion formula that is

imgGray = 0.2989 * R + 0.5870 * G + 0.1140 * B.

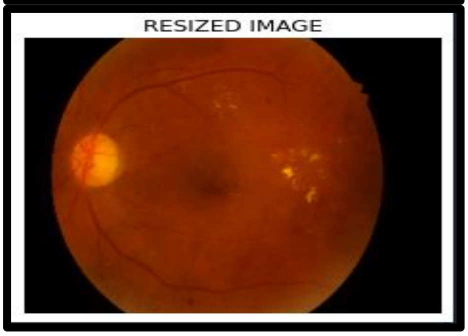


IMAGE SEGMENTATION:

In this step, we can segment the affected regions by using the ***morphological operations***.

- To segment the optic cup
- To segment the optic disk
- To segment the Exudates

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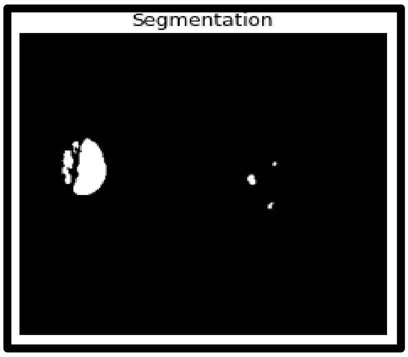
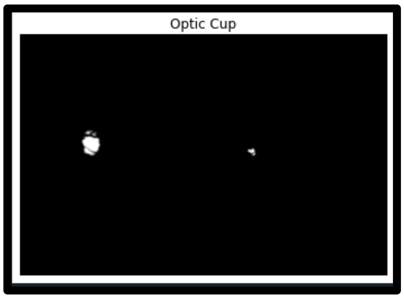


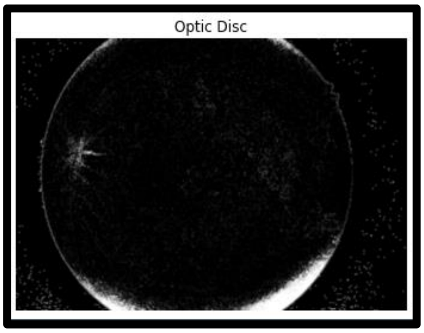
OPTIC CUP

The **optic cup** is the white, cup-like area in the centre of the optic disc. The ratio of the size of the optic cup to the optic disc (cup-to-disc ratio, or C/D) is one measure used in the diagnosis of glaucoma. Different C/Ds can be measured horizontally or vertically in the same patient. C/Ds vary widely in healthy individuals. However, larger vertical C/Ds, or C/Ds which are very different between the eyes, may raise suspicion of glaucoma. A C/D which enlarges vertically over months or years suggests glaucoma.



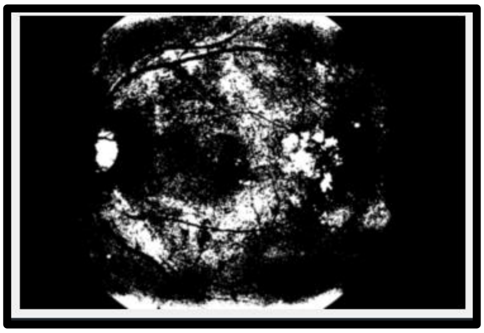
OPTIC DISK

The optic disc or optic nerve head is the point of exit for ganglion cell axons leaving the eye. Because there are no rods or cones overlying the optic disc, it corresponds to a small blind spot in each eye. The ganglion cell axons form the optic nerve after they leave the eye. The optic disc represents the beginning of the optic nerve and is the point where the axons of retinal ganglion cells come together. The optic disc is also the entry point for the major blood vessels that supply the retina. The optic disc in a normal human eye carries 1–1.2 million afferent nerve fibres from the eye towards the brain



EXUDATES

Exudate is fluid that leaks out of blood vessels into nearby tissues. The fluid is made of cells, proteins, and solid materials. Exudate may ooze from cuts or from areas of infection or inflammation. It is also called pus.



CONVOLUTION

A specific kind of such a deep neural network is the convolutional network, which is commonly referred to as CNN or ConvNet.(CNN) is having the framework of deep-learning algorithm used to extract the pixel-level features in a multi-layer form that are defined automatically from an image. CNNs model is used to understand the feature maps represented by an image CNNs is describing the best feature-map without manually defined domain-expert methodologies of image processing algorithms features defined by CNN model is known as deep-invariant features that are acquired from different layers also known as visual features

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RELU

The RELU layer applies the function f(x) = max (0, x) to all of the values in the input volume. The Rectified Linear Unit is the most commonly used activation function in deep learning models. This layer just changes all the negative activations to 0. RELU layers work far better because the network is able to train a lot faster (because of the computational efficiency) without making a significant difference to the accuracy.

POOLING LAYER

After some ReLU layers, programmers may choose to apply a **pooling layer**. It is also referred to as a down sampling layer. This basically takes a filter (normally of size 2x2) and a stride of the same length. It then applies it to the input volume and outputs the maximum number in every sub region that the filter convolves around

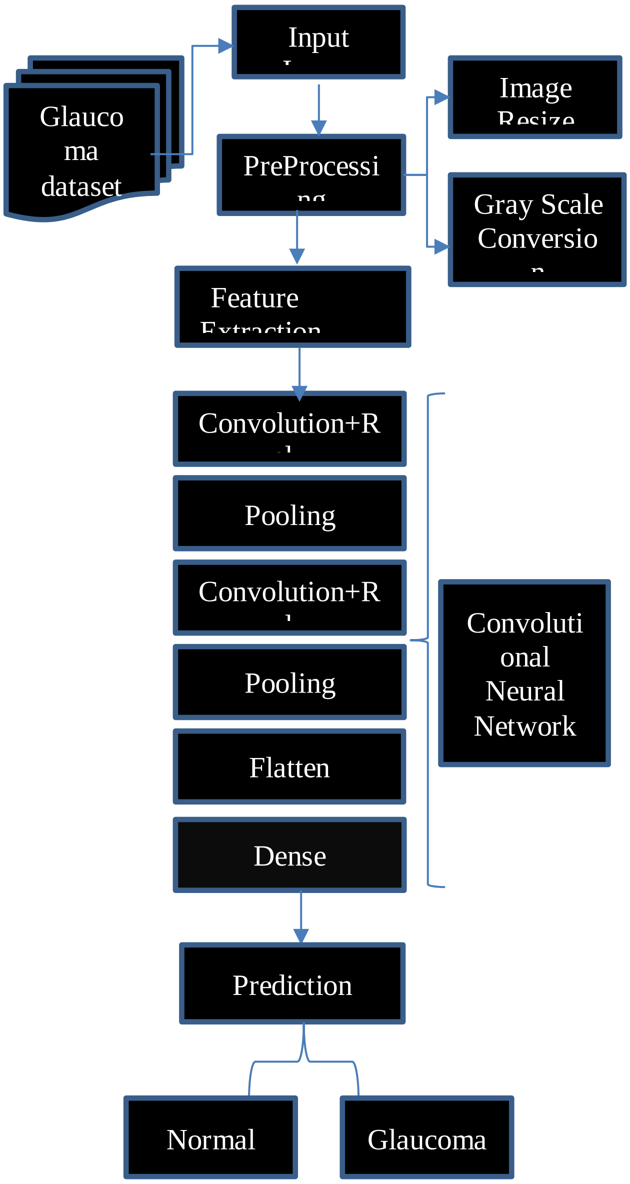
FLATTEN LAYER

Flattening is converting the data into a 1-dimensional array for inputting it to the next **layer**. **Flatten** the output of the convolutional **layers** to create a single long feature vector. And it is connected to the final classification model, which is called a fully-connected **layer**. Dense adds the fully connected **layer** to the neural network.

DENSE LAYER

Dense Layer is simple layer of neurons in which each neuron receives input from all the neurons of previous layer, thus called as *dense*. Dense Layer is used to classify image based on output from convolutional layers.

SYSTEM IMPLEMENTATION



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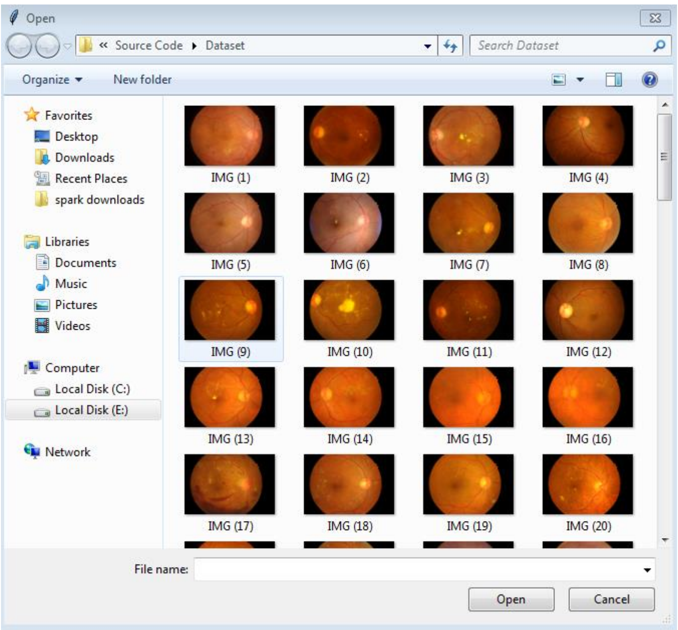
IMPLEMENTATION RESULT

The accuracy of this system is checked with the dataset which is publicly available.From this database we take the images and find the CDR value. Final Result will be generated based on the CDR value obtained.

DATASET



CLASSIFICATION:

```
3/3 [==============================] - 4s 66ms/step - loss: 38.7667 - accuracy: 0.5333
Epoch 2/30
3/3 [==============================] - 0s 58ms/step - loss: 26.5590 - accuracy: 0.6500
Epoch 3/30
3/3 [==============================] - 0s 54ms/step - loss: 5.7752 - accuracy: 0.4083
Epoch 4/30
3/3 [==============================] - 0s 61ms/step - loss: 5.1369 - accuracy: 0.3750
Epoch 5/30
3/3 [==============================] - 0s 55ms/step - loss: 1.7948 - accuracy: 0.6583
Epoch 6/30
3/3 [==============================] - 0s 56ms/step - loss: 1.7691 - accuracy: 0.6500
Epoch 7/30
3/3 [==============================] - 0s 59ms/step - loss: 0.9081 - accuracy: 0.6583
Epoch 8/30
3/3 [==============================] - 0s 52ms/step - loss: 0.7974 - accuracy: 0.5500
Epoch 9/30
3/3 [==============================] - 0s 55ms/step - loss: 0.8147 - accuracy: 0.5833
Epoch 10/30
3/3 [==============================] - 0s 54ms/step - loss: 0.6453 - accuracy: 0.6000
Epoch 11/30
3/3 [==============================] - 0s 53ms/step - loss: 0.6354 - accuracy: 0.6750
Epoch 12/30
3/3 [==============================] - 0s 55ms/step - loss: 0.6623 - accuracy: 0.6583
Epoch 13/30
3/3 [==============================] - 0s 55ms/step - loss: 0.6822 - accuracy: 0.6333
Epoch 14/30
3/3 [==============================] - 0s 52ms/step - loss: 0.6420 - accuracy: 0.6667
```

IMAGE NO	CDR VALUE OBTAINED	RESULT
Image no 1	0.70	Glaucoma
Image no 2	0.34	Normal
Image no 3	0.77	Glaucoma
Image no 4	0.23	Normal
Image no 5	0.75	Glaucoma
Image no 6	0.47	Normal

CONCLUSION

We conclude that, the dataset was taken from dataset repository as input and developed the deep learning algorithm such as Convolutional Neural Network.The CDR value is obtained from the image. Finally, we can predict the input image is normal or glaucoma.

FUTURE ENHANCEMENT

The further development of this project is to improve the accuracy. In the later versions we will develop pocket friendly applications where patients can check whenever they need.

REFERENCES

[1] Q. Liu, B. Zou, J. Chen, W. Ke, K. Yue, Z. Chen, G. Zhao G, A location-tosegmentation strategy for automatic exudate segmentation in colour retinal fundus images, Comput. Med. Imaging Graph. 55 (2017) 78–86.

[2] W. Kusakunniran, Q. Wu, P. Ritthipravat, J. Zhang, Hard exudates segmentation based on learned initial seeds and iterative graph cut, Comput. Methods Program Biomed. 158 (2018) 173–183

[3] A.B. Kadan, P.S. Subbian, Detection of hard exudates using evolutionary feature selection in retinal

fundus images, J. Med. Syst. 43 (7) (2019) 209.
[4] P. Khojasteh, L.A.P. Junior, T. Carvalho, E. Rezende, B. Aliahmad, J.P. Papa, D. K. Kumar, Exudate detection in fundus images using deeply-learnable features, Comput. Biol. Med. 104 (2019) 62.
[5] C. Huang, Y. Zong, Y. Ding, X. Luo, K. Clawson, Y. Peng, A new deep learning approach for the retinal hard exudates detection based on superpixel multi-feature extraction and patch-based CNN, Neurocomputing (2020)
[6] O. Ronneberger, P. Fischer, T. Brox, U-Net: convolutional networks for biomedical image segmentation, in: Medical Image Computing and Computer-Assisted Intervention (MICCAI), vol. 9351, Springer, LNCS, 2015, pp. 234–241. arXiv: 1505.04597
[7] X. Li, S. Chen, X. Hu, J. Yang, Understanding the Disharmony between Dropout and Batch Normalization by Variance Shift, J. Mach. Learn. (2018). arXiv: 1801.05134
[8] K. Bengler, K. Dietmayer, B. Farber, M. Maurer, C. Stiller, and H. Winner, ''Three decades of driver assistance systems: Review and future perspectives,'' IEEE Intell. Transp. Syst. Mag., vol. 6, no. 4, pp. 6–22, Oct. 2014.
[9] . Vallabha; R. Dorairaj; K. Namuduri; H. Thompson "Automated detection and classification of vascular abnormalities in diabetic retinopathy" 58, pp. 749–759, Sep. 2015.

[10] M. J. M. Sullman, L. Dorn, and P. Niemi, ''Eco-driving training of professional bus drivers—Does it work?'' Transp. Res. C, Emerg. Technol., vol. 58, pp. 749–759, Sep. 2015.
[11] C.-H. Lee and C.-H. Wu, ''An incremental learning technique for detecting driving behaviors using collected EV big data,'' in Proc. ASE BigData SocialInform., 2015, p. 10.
[12] J. Négre and P. Delhomme, ''Drivers' self-perceptions about being an ecodriver according to their concern for the environment, beliefs on ecodriving, and driving behavior,'' Transp. Res. A, Policy Pract., vol. 105, pp. 95–105, Nov. 2017.
[13] J. L. Jimnez-Palacios, ''Understanding and quantifying motor vehicle emissions with vehicle specific power and TILDAS remote sensing,'' Ph.D. dissertation, Massachusetts Inst. Technol., Cambridge, MA, USA, 1999.
[14] M. Barth, F. An, T. Younglove, G. Scora, C. Levine, M. Ross, and T. Wenzel, ''NCHRP PROJECT 25-11: Development of a comprehensive modal emissions model,'' in Proc. 7th CRC Road Vehicle Emissions Workshop, 2000, pp. 1–6.
[15] N. Davis, J. Lents, M. Osses, N. Nikkila, and M. Barth, ''Development and application of an international vehicle emissions model,'' Transp. Res. Rec., J. Transp. Res. Board, vol. 1939, no. 1, pp. 156–165, 2005