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High level design to diagnosis glaucoma using CNN

Nandha Kumar R
Associate Professor Gr-II, School of CSE, VIT AP University, Amaravati -522237, AndhraPradesh
Corresponding author email: nandha.r@vitap.ac.in

Sudhakar Ilango S
Associate Professor Gr-II, School of CSE, VIT AP University, Amaravati -522237, AndhraPradesh
Email: sudhakar.ilango@vitap.ac.in

***Abstract*---**To minimize long-term structural damage and irreversible visual loss, glaucoma must be diagnosed early. Glaucoma is diagnosed by assessing visual activity as well as monitoring structural damage to the optic nerve. Transparent laser ophthalmoscopy scanning, and laser polarimetry are examples of computer-based equipment that can aid in the analysis of visual acuity and structure. Most persons with glaucoma do not experience any early signs or pain. Glaucoma must be diagnosed and treated by an eye doctor on a regular basis. Traditional glaucoma detection procedures include an eye doctor analyzing photographs and looking for irregularities. Because the image contains noise and other elements that make appropriate analysis difficult, this method takes a long time and is not always precise. In addition, a machine that has been educated for analysis becomes more accurate than a human analyst. The proposed method will automate this procedure by employing deep learning techniques in image processing to diagnose glaucoma without the need for human intervention.

***Keywords*---**high level design, diagnosis glaucoma, CNN.

Introduction

Today technology play a major role in all kind of fields from agriculture, medicine to new planet discovery. Even through there is tremendous improvement in technology, may things will influence the human directly or indirectly, which intern created more hazardous to human lifestyle. There are many technology improvements happen in medical fields even though there is no proper diagnosis

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to identify or predict the growth of different infection in our human body. One among them is the glaucoma which will damage your optical nerves system and make human being become blindness. It is difficult to identify the glaucoma at the initial stage based on some symptoms, because nerve optical system consists of millions of tiny nerves fibers. It transfers signal for the visions with help of different tiny nerves cables. This nerves actively transfers the signal when there is a fluid contain on that spot, if fluid content drains it leads to different issues such as nerves cable won't response signal properly, sometime nerves cable fails to carry signals. It makes human eye stop functioning all kind of signal suddenly. There are different types of glaucoma: open angle and closed angle. It is difficult to identify the open angle glaucoma because no changes in the vision until there is a severe damage on your sight. Closed angle glaucoma happen when your iris is very close to the drainage angle. It completely blocks which intern increase the eye pressure.

- To minimize long-term structural damage and irreversible visual loss, glaucoma must be diagnosed early.
- Glaucoma is diagnosed by assessing visual activity as well as monitoring structural damage to the optic nerve.
- Transparent laser ophthalmoscopy scanning, and laser polarimetry are examples of computer-based equipment that can aid in the analysis of visual acuity and structure.

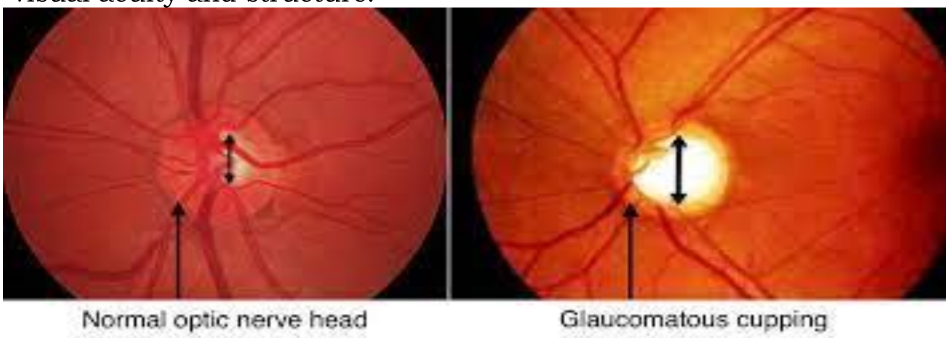


Figure 1 Glaucoma Negative vs Glaucoma Positive

In order to find the tiny nerves, signal transmission and connectivity, a physician has to check each FUNDUS image manually to detect the presence of Glaucoma but doing so would take up a lot of time. Instead of a doctor spending time analyzing the images, he/she can be using that to prepare a medication process in order to treat the patient. The physician can compare the similar glaucoma patient monitoring report and the nerves stresses, drain of fluid, or drain angle change easily. It will give more information for the physician to diagnosis the patient. The proposed method will automate the process of detection using deep learning methods. In the existing methods, different vision symptoms are identified using different chronic weaknesses. Different diagnostic capabilities are considered to identify the stress in the optical cups, vertical rim area, and thickness. The estimation of the visual field varies with different age groups and different coherence tomography sources.

Proposed method

High level design to diagnosis glaucoma

The proposed High-Level Design to Diagnosis Glaucoma (HLDDG) explains the architecture that will be used for developing the HLDDG method. The architecture diagram provides an overview of the entire system, identifying the main components that would be developed and their interfaces. The HLDDG uses non-technical to mildly technical terms that will be understandable to the user. The proposed model initially collects different types of images of glaucoma as a master dataset. From the collected image few images are trained with different futures, which can able identify all the types of glaucoma. Once the image is trained then it will tune based on updated information or any change in storing weights in the training model. This storing weight computation help to locate and detect glaucoma. Tuning model updates their model and weight futures based on newly uploaded images of similar types

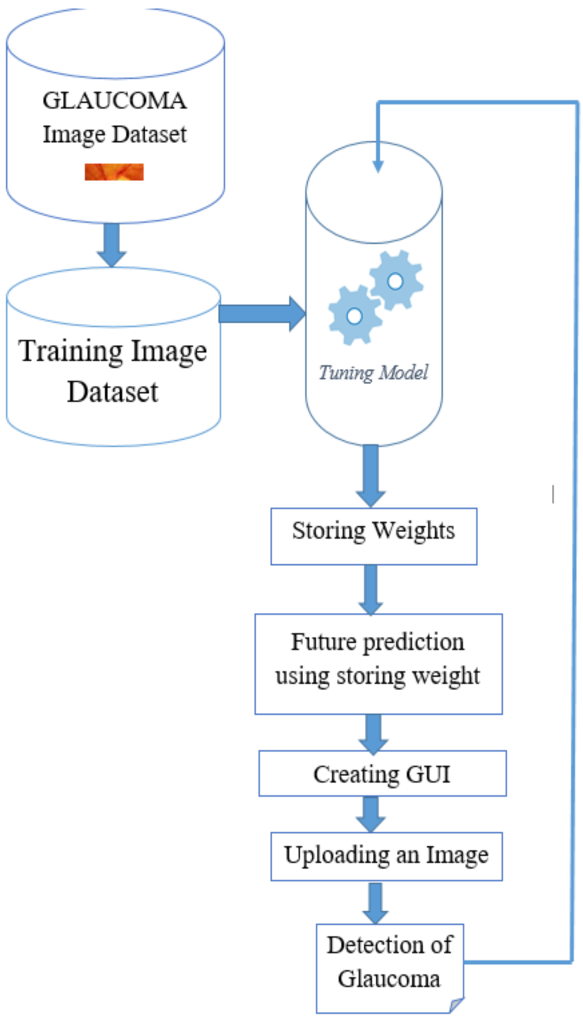


Figure 2 High Level Design to Diagnosis Glaucoma Model

The proposed HLDDG model consists of different steps to diagnosis glaucoma disease: Initially the HLDDG model is trained based on the previously available dataset of similar infections. Dataset consists of both types of images glaucoma positive and negative image. This proposed model will undergo various convolution and pooling layers to fine tune the in-depth of nerves connectivity and fluid content of the eye. Model turning helps to understand or learn the depth variation of the different images. It will give clear variation about each and everchangees of the image. It is will more useful for the physician to diagnosis the patient current infection stage. It will in turn yield high accuracy in the minute variation in the images. Different weight is stored if different situation to simulate the difference in a more accurate manner. This per stored image helps the physician to detect the infection clearly in various stages of the disease.

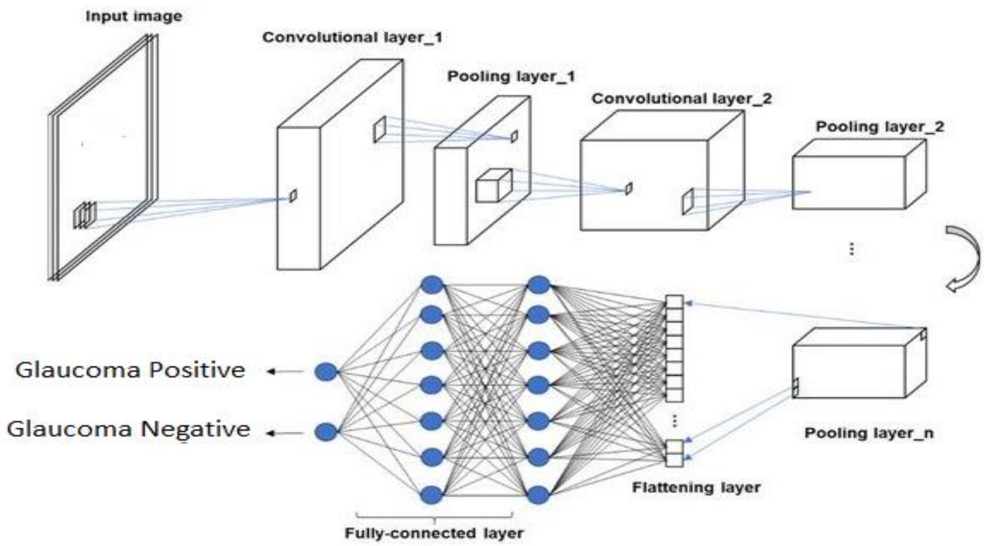


Figure 3: Block Diagram of the Algorithm implemented

From the input image, the proposed HLDDG model extracts the important features of each image and stores the weight. This stored weight will give information about different types of tiny fluids available at different stages in glaucoma with influence the human being slight.

HLDDG Model

- Conv2D layer (filter=32, kernel_size=(3,3), activation=”relu”)
  In this layer convolution operation takes place, also called as filter. Here high level features of the image are extracted.
- MaxPool2D layer (pool_size=(2,2))

Here dominant features are extracted.

- another Conv2D layer (filter=32, kernel_size=(3,3), activation=”relu”)
- MaxPool2D layer (pool_size=(2,2))
  We are using another Convolution layer and then max pooling.

- Flatten layer
- Dense Fully connected layer (128 nodes, activation=”relu”)
- Dense layer (1 node, activation=”sigmoid”)
  Now we are flattening the layer and then using fully connecting layer we are classifying our image

Results and Discussion

The proposed model used the ACRIMA dataset, it is a publicly available dataset. We collected different sample images from various forums to extract the features more accurately. We collected and classified the image based on different criteria with different stages example humans with different age groups and with different pre diagnosis of diseases patients. After undergone pre-processing for different pixel normalization. Weight is stored with different criteria. The number of epochs is set after tuning to yield better results and accuracy. A simple GUI is created. Here we load the previously saved model weights to predict the result of the new image. We use the upload image button to upload the image and then click on classify to get the result.

Output

```
Console 1/A
16/16 [==============================] - 99s 6s/step - loss: 0.5842 - accuracy:
0.7461 - val_loss: 0.5508 - val_accuracy: 0.7500
Epoch 23/30
16/16 [==============================] - 96s 6s/step - loss: 0.5966 - accuracy:
0.7398 - val_loss: 0.5751 - val_accuracy: 0.7500
Epoch 24/30
16/16 [==============================] - 96s 6s/step - loss: 0.5710 - accuracy:
0.7398 - val_loss: 0.5891 - val_accuracy: 0.7188
Epoch 25/30
16/16 [==============================] - 95s 6s/step - loss: 0.5746 - accuracy:
0.7459 - val_loss: 0.4464 - val_accuracy: 0.8438
Epoch 26/30
16/16 [==============================] - 95s 6s/step - loss: 0.5819 - accuracy:
0.7439 - val_loss: 0.5485 - val_accuracy: 0.7812
Epoch 27/30
16/16 [==============================] - 98s 6s/step - loss: 0.5705 - accuracy:
0.7520 - val_loss: 0.5285 - val_accuracy: 0.7812
Epoch 28/30
16/16 [==============================] - 95s 6s/step - loss: 0.5772 - accuracy:
0.7377 - val_loss: 0.6024 - val_accuracy: 0.7188
Epoch 29/30
16/16 [==============================] - 95s 6s/step - loss: 0.5718 - accuracy:
0.7500 - val_loss: 0.5269 - val_accuracy: 0.8125
Epoch 30/30
16/16 [==============================] - 94s 6s/step - loss: 0.5775 - accuracy:
0.7377 - val_loss: 0.6689 - val_accuracy: 0.6562
C:\Users\91916\Desktop\varun\Project\untitled3.py:55: UserWarning:
`Model.evaluate_generator` is deprecated and will be removed in a future version.
Please use `Model.evaluate`, which supports generators.
  score = model.evaluate_generator(test_set,40/batch_size)
 Total:  130
Loss:  0.5752179622650146 Accuracy:  0.75
```

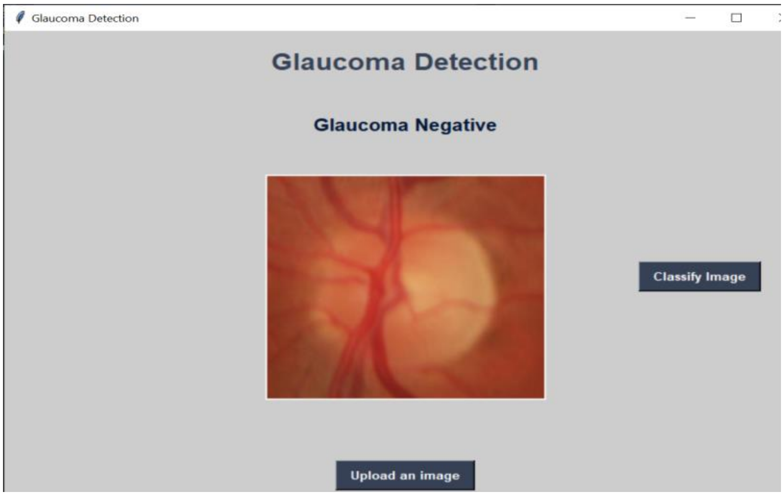
Displaying accuracy. The accuracy of the model is 78%

```
score = model.evaluate_generator(test_set,batch_size)
print(" Total: ", len(test_set.filenames))
print("Loss: ", score[0], "Accuracy: ", score[1])
```

Output

```
  score = model.evaluate_generator(test_set,40/batch_size)
 Total:  64
Loss:  0.37149080634117126 Accuracy:  0.78125
IPython console  History
LSP Python: ready   conda (Python 3.8.8)   Line 44, Col 34   ASCII   CRLF   RW   Mem 72%
```

Choose an image and click on classify button to get results



HLDDG model detected image

Conclusion and future work

The proposed HLDDG model detects Glaucoma with an accuracy of 78%. We are currently using a simple GUI to test the accuracy of the model. Presently the model is designed to detect glaucoma after a person is glaucoma positive but in future, the aim is to design a model that can predict glaucoma even before the person actually gets infected by glaucoma.Also, to gather a strong dataset to increase accuracy further. Then for further scope is to create a mobile or web application where real time detection can be done.

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