WWW.IJRPR.COM

**International Journal of Research Publication and Reviews**

Journal homepage: www.ijrpr.com ISSN 2582-7421

# Glaucoma Detection Using Deep Learning

***Sneha Suresh Vanjire[1], Sreelakshmi[2], Merin Meleet[3]***

[1.]R.V. College of Engineering ,Bengaluru,India
[2.]R.V. College of Engineering Bengaluru,India
[3]R. V.College of Engineering Bengaluru,India
[1]snehasureshv.is18@rvce.edu.in[2]sreelakshmi.is18@rvce.edu.in[3]merinmeleet@rvce.edu.in

ABSTRACT

Glaucoma is a persistent eye disease which may lead to vision impairment that is irreversible. Highlighting the importance of early detection of the disease, this research investigates the potential of establishing an automated feature learning technique for detecting glaucoma and its severity level in retinal fundus images through deep learning. To identify between distinct stages of Glaucoma, a CNN based fully automated system has been proposed. Our work is mainly divided into two parts.The first part is training, in which the model is trained on a dataset. The second phase is inference, in which our model is put into action by feeding live data to produce an output.

*Keywords*—Deep learning, glaucoma, neural network, fundus, optic nerve, CNN, Image processing, Retinal Fundus images .

## INTRODUCTION

Glaucoma refers to the condition wherein the optic nerve of the human eye is damaged which leads to vision loss or blindness. This condition occurs as various levels of vision impairment which eventually might result in permanent blindness if not detected in the early phase. According to the WHO, glaucoma has been globally declared as the major cause of blindness after cataract.

This condition causes irreversible damage. Therefore, it's important to have regular eye check ups so that it is detected at early stages and treated accordingly.

The neuro retinal rim is the annular zone between the optic cup boundary and the optic disc that represents the retinal nerve fibres. Intraocular pressure refers to the fluid pressure within the eye's inner chamber (IOP). Increased IOP causes an obstruction of the aqueous humour outflow. The optic nerve, which transmits signals from the retina to the human brain, is damaged as a result. The thickening of the retinal nerve fibre layer (RNFL) as a result of the degeneration of optic nerve fibres is known as cupping. Glaucoma progresses as a result of thiscupping.

Cup to disc ratio (CDR) is a value through which we determine the presence and severity of glaucoma as it detects the depletion of healthy Neural Retinal tissues. A healthy eye usually has a CDR of 0.3 orless.

Clinical diagnosis of glaucoma by the evaluation of CDR by an opthalmologist is time consuming and subjective. Moreover, the availability of the clinical equipment to carry out this procedure is limited. Therefore, Digital retinal fundus images prove to be of high potential to be utilized to detect and observe the progression of glaucoma. Computer aided diagnosis of these images helps to diagnose this condition using various computational algorithms without having to worry about inter and intra observer variability that is usually seen in clinical diagnosis.

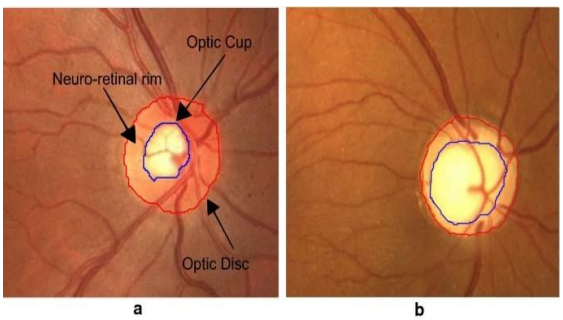


Fig 1: Retinal fundus images cropped around the region of optic disc. a. Optic disc in a normal eye and b Optic disc in a glaucoma infected eye

## LITERATURE SURVEY

In 2020, a decipherable pipeline to detect glaucoma using retinal fundus images was proposed which should be able to run on mobile devices in [1]. In this work, multiple open-source datasets were clustered to train the CNN model to perform cup to disc segmentation and classification. The pipeline was developed as a mobile application and performance of this pipeline was evaluated based on time and space complexities of the application.

Recently, in a study conducted in a field of ophthalmology, 86,123 pair of retina fundus images along with SDOCT images were collected from 5529 glaucoma patients or suspects to scrutinize if thickness of RNFL can be used to detect the progression of glaucoma by time[2]. A deep learning based CNN was proposed to evaluate the images to find the thickness of RNFL. The model was also tested on various independent data samples. The major motive of this work was to analyze how a change in RNFL thickness affects SD OCT thickness over time.

In 2019, research was done to analyze the role of ONH- Optic Nerve Head in progression of glaucoma[3]. Various other distances were calculated along with cdr ratio from the obtained OD AND OC Values. All these distances are very important indicators of the disease. The mechanism proposed in this work was tested on a private dataset which achieved an accuracy of94%.

An automated system for the detection of 3 stages of glaucoma utilising the retinal fundus images of the human eye was proposed in [4] which made use of GoogLeNet and ResNet-50 architectures for training and classification using transfer learning. Different datasets were used for training and testing purposes to combat the issue of small datasets. GoogleNet performed better than Resnet-50 in this work.

A study was conducted in 2019 to test the theory of baseline optical coherence tomography being able to predict the development of visual field in a group of glaucoma suspected patients and its performance was evaluated based on semiquantitative optic disc measures[5]. This research took place in a university setting. It was conducted on the data of 95 suspects..The key outcome measure was the ability of trend and event analysis to predict glaucomatous VF worsening.

The purpose of [6] is to use deep learning algorithms to detect glaucoma and to reduce redundancy in training dataset to improve the accuracy and efficiency. An AG-CNN architecture is proposed and a large database is prepared with a good number of images in both the categories i.e., glaucoma and non-glaucoma. Feature extraction and attention maps were adopted to enhance the performance of themodel.

A deep learning based CNN which makes use of two different architectures jointly for the segmentation of optic disc and optic cup was proposed in [7].The system was made to test on a collection of 50 images. The proposed mechanism was able to achieve an accuracy of 95% and 93% for cup and disc segmentationrespectively

A generic deep learning model was proposed in 2019 in [8] where the dataset was a combination of more than one dataset and the models were trained based on multiple architectures and methodologies. The model was able to achieve an accuracy of around 80%. The dataset contained retinal fundus images of the human eye.

A study was conducted in 2019, with the aim of developing a deep learning algorithm for the detection of open angle glaucoma using a 3-D optical topographytechnology[9].

The data for this study was collected using a spectral domain OCT and a total of 200 images in glaucoma and 150 images in non-glaucoma were gathered. Deviation maps were utilized for better performance. Transfer learning techniques were employed with various forms of the images like grey scale, RBG etc. AUC scores were used to evaluate the proposedsystem.

Many different CNN models were studied and a six-layered architecture was presented in [14]. SCES and the ORIGA datasets were utilized in this work. The model was experimented on each dataset separately and then compared. An accuracy of 82% was obtained for the SCES dataset and an accuracy of of 88% for the ORIGA dataset. Dropout methodology was used for effective performance.

## ARCHITECTURE

Deep learning techniques are used to classify images. It combines feature extraction and categorization into one system. Using complicated networks established with vast amounts of data, these methods can produce promising outcomes. In this work, we present a unique CNN architecture for automatically detecting various phases of glaucoma. During the training part, features are deduced from the input images to yield a robust CNN model. This model is then tested to classify images from the testing folder. The detailed information about the architecture of the proposed model is described below:

A CNN model is built from various layers such as convolution layer, max pooling layer etc. The number of layers depends on the size of the data to be trained. The architecture of our model is as shown in Figure 2 :

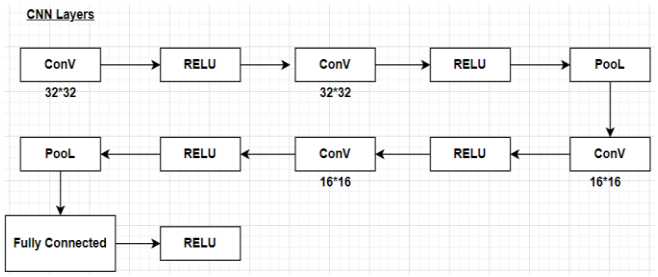


Fig 2: Model Architecture

We attempt to achieve the best outcomes with the fewest layers possible by efficient selection of network parameters. The various layers of our CNN model are given below:

*A. Convolutionallayer:*

This layer applies filters to the input called convolution which results in activation. Convolution results in generation of feature maps which are then fed as an input to the following layer.

*B. Batch normalizationlayer:*

This layer has the ability to improve overall performance as well as learning speed. It also permits the transfer of normalised data samples among the intermediate layers,which inturn accelerates the total learning process due to improved learning rates.

*C. Activation FunctionLayer:*

Activationfunctionsappliedbythislayertotheoutputof the convolution layer that helps the network to learn intricate patterns in the data. Examples of activation functions include RELU, Tanhetc.

*D. Rectified Linear Unit(ReLu):*

This is the portion where each input undergoes a thresholding function, in which any negative value is modified to zero. This lowers data redundancy while preserving key features. This layer's output is the same size as the preceding one's.

*E. Max poolinglayer:*

The function of this layer is to minimise the size of each feature map by applying maximum pooling. Stride value is normally set as per the user. The highest value over the window is taken into account, and that figure is used to replace the window. The output here is smaller than that of the preceding layer.

*F. Soft-maxlayer:*

The input data is subjected to a soft-max function in this layer. It aids in the reduction of outliers without their removal from the input images.Figure 3 shows the inner structure of each block where the input image passes through activation function - RELU and then passes through a fully connected layer and ultimately the result is obtained after tuning through the softmax layer.

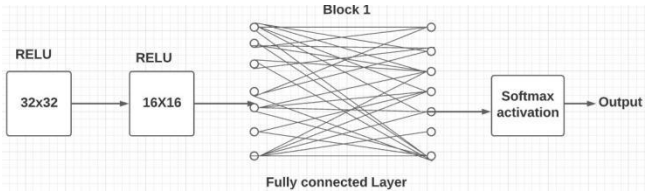


Fig 3: **Structure of each block**

Our model consists of 4 convolution layers each followed by the activation function ReLU and batch normalization layer.Each set is applied a dropout of size 0.25 and a max pooling of size (2,2). And finally the architecture ends with a softmax classifier applied to the final layer.

## METHODOLOGY

*A. DATASET*

We have searched the web for retinal fundus images of the eye with labels. We finally stuck to the dataset provided by the Harvard Dataverse, which is an open source data hub. Our dataset contains retinal fundus images of glaucoma patients or suspects. These photographs are a pre-processed version of rawdata:

Pre-processingstep:

1) All the images are scaled to a fixed size i.e., 800pixels.
2) All the images are cropped to 250 pixels at the region of the opticnerve.

These fundus photographs are sourced from a Hospital.

The original dataset contains 467 images in the category of advanced glaucoma, 289 in the category of early glaucoma and 788 in the normal category. To balance the images in all the folders we've considered to take 289 images in each category.

*B. Data pre processing*

*a. Datalabeling*

All the data fits into three categories : normal, early and advanced. The class labels are extracted from the file name in the dataset directory.

*b. Imageresizing*

All the images are resized to a fixed size of 32*32 pixels.

*c. Imagescaling*

The data is converted into a numpy array and preprocessed by scaling all the pixel entities in the range [0,1]

*d. One-hotencoding*

The current labels which are strings are converted into integers and one hot encoded.

*e. Dataaugmentation*

In deep learning, a lot of images are needed for better results. So, we have augmented the images using keras preprocessing tool. It generated many augmentations of each image while training for decreasing the variance of the model. Data augmentation also includes several processes like horizontal flip, vertical flip, random rotationetc.

*C. Training*

Adam optimizer is used to compile the model and it is passed to the model by a string identifier with appropriate learning rate and epochs.The dataset is partitioned into two folders: training and testing folders using train/test split leaving 75% of the data for training and 25% for testing.Sequential model API is used to build the model. The training process of our model is as shown in figure 4.Various combinations of batch size and epochs were experimented to analyze the performance pattern of the model corresponding to each set. After a few rounds of trialand error the values were finalized. The batch size was set to 8, the number of epochs was set to 200 and the initial learning rate was(1e-4). Then the model was set to train on the dataset where the images from each category are fed to the model with corresponding labels for classification.

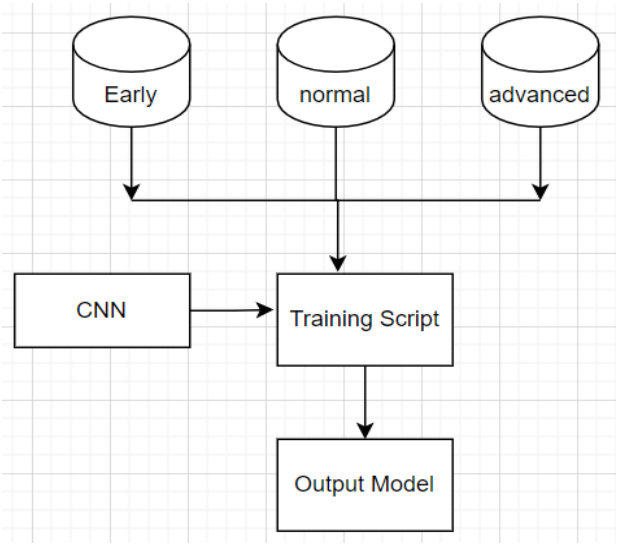


Fig 4: Training model: Our CNN model is trained on our dataset setting all the appropriate values of batchsize andepochs

## RESULTS

The evaluation of our model was done based upon various parameters as shown in table 1. All the parameters were segregated for each class and displayed after the training process.Precision tells us what percentage of the positive predictions were genuinely correct. The precision values obtained for our model for each category show that most of the images in the normal category were correctly classified with a precision of 97% and early glaucoma being classified with least precision of66%.The recall values obtained are satisfactory and the support values show that our model is quite balanced.

Table 1: **Training results for each category**

| | PRECISION | RECALL | F1-SCORE | SUPPORT |
|---|---|---|---|---|
| advanced | 0.84 | 0.75 | 0.79 | 63 |
| early | 0.66 | 0.87 | 0.75 | 71 |
| normal | 0.97 | 0.76 | 0.85 | 76 |
| accuracy | | | 0.80 | 210 |
| macro avg | 0.82 | 0.79 | 0.80 | 210 |
| weighted avg | 0.82 | 0.80 | 0.80 | 210 |

A validation accuracy of 80% and weighted avg of 0.80 was obtained through this methodology.A testing folder is created with 13 images from the dataset to test the model in real time. The division is such that 25% of the images from the dataset are used for testing and 75% for the training.
Graphs are plotted to visualize the results after training. The Loss and Accuracy vs epoch graph is shown in figure 5. The number of epochs are represented on X-axis and the accuracy/loss for each epoch on Y-axis.Training and validation loss seems to decrease with each epoch and the train and validation accuracy increases for the same.As evident from the graph, the curve started to flatten when reaching 200 epochs. As there was no further improvement in the performance or accuracy, the epochs were stopped once the curve started flattening.

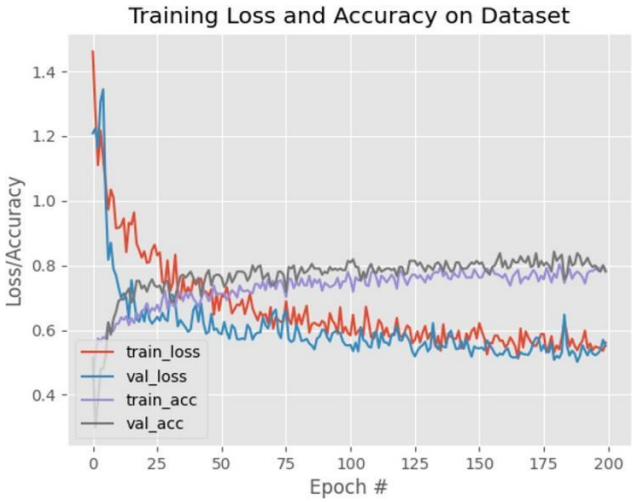


Fig 5: The loss/ accuracy vs epoch graph. number of epochs are represented on X-axis and the accuracy/loss for each epoch on Y-axis

Finally the results were verified using inference techniques where each image is fed to the code from the testing folder and the result is cross checked. Our model was able to detect the category of most of the images correctly.

## CONCLUSION

A novel CNN model based on deep learning is proposed for the computer aided diagnosis of glaucoma in this work. The mechanism proposed in this paper is developed on a seven-layered architecture, and it utilizes the patterns drawn to categorize glaucoma into various stages based on its severity i.e., normal, early and advanced glaucoma using the fundus images. The dataset was collected from the Harvard dataverse; A validation accuracy of 80% was obtained from the proposed methodology. The values are obtained for each category and compared. Finally the results were tested using inference techniques to see if the model is working as expected. The only limitation is the availability of a large dataset. The work done here was just with less than 300 images in each category. Given a dataset with anample number of images, the performance of the model can be further improved. Also it can be further improved to accommodate one more class i.e., moderate glaucoma provided we have the dataset with a good number of images in

the category. A computerized solution for classification of various stages of glaucoma is proposed and this can be potentially used for the diagnosis of glaucoma using digital fundusimages.

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