Perspectives in Communication, Embedded-Systems and Signal-Processing (PiCES) – An International Journal
ISSN: 2566-932X, Vol. 4, Issue 9, December 2020
Part of the Proceedings of the 1st All India Paper writing Competition on Emerging Research - PaCER 2020

Early and Efficient Detection of Glaucoma Using Image Processing and Deep Learning

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***Abstract:** A Chronic eye disorder called glaucoma leading to irreversible blindness by damaging the optic nerve of the eye. It is provoked due to exalted intraocular pressure inside the eye. Detecting glaucoma is the most challenging process in case of open angle glaucoma (OAG) due to lack of initial symptoms. Detecting glaucoma in the early stage is required to facilitate appropriate monitoring, treatment, and to diminish the likelihood of vision loss. In this paper, we propose a method to analyse and categorize the fundus image as glaucomatous or healthy image by considering cup to disc ratio using image processing techniques and feature extracted through Deep learning. The assessment of CDR is the foundation to detect glaucoma, the CDR value will increase from 0.6 – 0.9 when affected by this disease. In order to consider other medical parameters for glaucoma detection and to automate the detection process Deep Learning-Convolution neural network model is implemented. Overfitting is avoided by adopting data augmentation technique. To make the system user friendly and interactive Graphical user interface (GUI) application is developed. The system is trained and the results demonstrate that the technique had a good accuracy in classifying the fundus images as healthy or glaucoma.*

***Keywords:** Glaucoma; Fundus images; Open angle glaucoma (OAG); Cup to disc ratio (CDR); Deep learning algorithms; Convolutional neural networks; Graphical User Interface (GUI)*

I. INTRODUCTION

Vision is essential in everyone’s life to visualize the things around us but there is vision loss in many people due to few eye related diseases. According to 2019 survey of World Health Organization, 2.2 billion people are suffering from several eye related diseases among which 39 million people are completely blind. The overall percentage of the eye diseases which causes blindness are 47.8% is due to cataract, 12.3% for glaucoma, 8.7% for age related macular degeneration, 4.8% of diabetic retinopathy, 5.1% due to corneal opacities. Major challenging task is to detect glaucoma in the early stages which is the second main cause for the vision loss worldwide. Glaucoma is a chronic disease which develops and progresses slowly and finally leads to blindness if not treated early. So, it is called as silent thief of vision. Glaucoma patients cannot recognize the vision impairment during the initial days, later the disease progresses gradually leading to complete vision loss. Optic nerve deterioration takes place due to glaucoma [2]. Glaucoma symptoms are painless and leads to vision loss in the final stages. Hence, early detection is required in order to prevent the vision loss. Eye consists of two types of fluids namely vitreous humor and aqueous humor. Aqueous humor has a stable intra ocular pressure (IOP) of 21 mmHg and to maintain stable IOP, aqueous humor is periodically secreted and drained out. Sudden increase in the IOP takes place due to blockage of channels where aqueous humor is not drained out. Now, the pressure inside the eye will be more than 21 mmHg which leads to more pressure on the optic nerve fibers [3]. Nerve fibers gets damaged due to the elevation in the IOP causing glaucoma disease. Due to glaucoma, blood vessels get flattened and cup area of the optic nerve increases with constant optic disc area so that cup to disc ratio (CDR) enhances. This disease can also occur due to poor blood regulation to the optic nerve in the presence of normal eye pressure.

Glaucoma is associated with vision impairment due to the damage of the optic nerve fibers, therefore it is termed as optic nerve disease, where optic nerve acts as a mediator between the eye and brain to visualize by sending and receiving the message signals. So, if optic nerve gets damaged then brain cannot receive and send signals to eye and vice versa. The two types of Glaucoma are open angle and closed angle (angle closure) glaucoma. Open angle glaucoma is painless and has no symptoms and develops progressively. Closed angle glaucoma has symptoms such as nausea, vomiting, redness and symptoms likely caused due to the sudden increase in the IOP. Angle between iris and cornea is the irideocorneal angle used to differentiate closed angle and open angle glaucoma. Vision loss can be prevented by detecting glaucoma in the early stages. Currently, OCT (Optical coherence Technique) and HRT (Heidelberg retinal Tomography) are the techniques used for the detection of glaucoma. OCT scanning is the currently used technique for detecting glaucoma depending on energy levels [1]. In OCT scanning low coherence light is utilized for imaging of cross-sectional view of the retina. Images obtained from the OCT scanning may be two or three dimensional. HRT is a technique used to capture the optic nerve by using lasers to get three dimensional images. This technique makes use of inner layers of the retina that forms the optic nerve, when person is affected by glaucoma, cells forming optic nerve fibers gets damaged due to which the region where optic nerve get damaged, optical cupping will occur. The depth of the cupping is examined by the ophthalmologist to detect glaucoma. But two techniques used are prolonged and expensive. So, many ophthalmologists use fundus images for diagnosis of glaucoma. Fundus images are captured using fundus camera. Fundus images are the two-dimensional images of the retina. Fundus images contains macula at the center and optic disc either on the left or right side depending on left eye or right eye. The color of these images is orange color due to the presence of rhodopsin pigment and complexes of vitamin B12 and intensity of this color gets diminished as the age of person increases. Healthy and glaucoma image are shown in Fig 1 and Fig 2 respectively.

Fig 1. Healthy Fundus Image

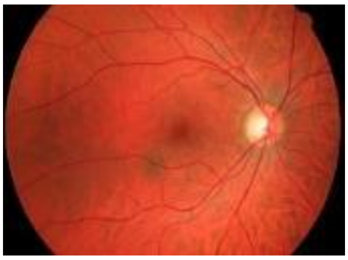


Fig 2. Glaucoma Image

Glaucoma can be determined using shape, size and structure of the optic cup and disc of the retinal fundus image. Some parameters to detect glaucoma are CDR, ISNT rule and energy levels. For a healthy person cup to disc ratio will be 0.5 and greater than 0.5 for glaucoma affected person [6]. ISNT is abbreviated as Inferior, Superior, Nasal and Temporal regions of NRR. In this paper, glaucoma is detected in the early stages more accurately by estimating cup to disc ratio to recognize the disease efficiently. Fundus images are used for the calculation of areas of optic disc and cup. This paper is organized into different sections where each will give brief description about the process of detection of glaucoma. First section will give the brief introduction to the disease glaucoma followed by literature review will give the existing technologies for detecting glaucoma. Proposed method is described in third section which will give the image processing and machine learning concepts for diagnosis of glaucoma followed by results of the glaucoma detection. Comparison of the machine learning models and later implementing on the GUI is given in the following sections. Conclusion is given the seventh section.

II. LITERATURE SURVEY

Hina Raja etal [1] presented a novel method for detecting glaucoma, computing cup to disc ratio by using OCT scanned images i.e. spectral domain (SD OCT) images. Optic cup diameter is extracted using the inner limiting membrane (ILM) and optic disc diameter has been obtained using Retinal Pigment Epithelium (RPE). The two layers of the SD OCT images are ILM and RPE. Initially the region containing cup i.e. ILM layer is separated earlier to extraction of the Retinal Pigment Epithelium layer to calculate diameter of the cup. Since green channel is more prominent with cup and disc region. Further green channel is used for extraction of cup and disc diameter. First, cup diameter is computed depending on the threshold value then after disc diameter is calculated by removing ILM layer, afterwards applying threshold for 5-levels then RPE layer is extracted after processing RPE layer for calculation of disc diameter. After calculating cup and disc diameter, CDR is evaluated for the computed cup and disc diameter.

Javeria Ayub etal [2] has come up with a method for detecting glaucoma automatically by utilizing CDR from retinal fundus images. For the enumeration of CDR, in the first instance ROI is extracted using weights of the centroid depending on the intensity of the pixels. Later preprocessing tasks are performed after that k-means clustering is applied in order to make clusters of intensity pixels values to recognize optic disc and cup. Borders of the optic cup and disc are detected using ellipse fitting. Further CDR value is calculated to distinguish healthy and glaucoma affected images.

Mahida Naveed etal [3] come up with different techniques for detection of glaucoma. For the extraction of the required regions for the detection process like textural features, features based on intensity are selected for the categorizing the disease detection process. OCT and fundus images are used for the analysis. SD-OCT is used for the estimation of CDR. OCT is a technique used to classify glaucoma images depending upon the energy levels. Fundus images are also used for the analysis and finally comparison is made between OCT and retinal fundus images for glaucoma identification.

U. Raghavendra etal [8] has propounded a different method of detecting glaucoma using deep convolutional neural networks. This is a novel method of recognition of glaucoma using CAD (Computer Aided diagnosis) which is a non-intrusive technique for identification of glaucoma in the initial stages using digital fundus images. This system is developed using large dataset to get more accurate and efficient results by using CAD tool to implement deep learning technique. Using deep learning, 18 layers of convolutional neural networks, fundus images are classified as glaucomatous or healthy by extracting the features required. By training the model robustly, they are achieving the more accuracy and increase in the performance factor.

III. PROPOSED METHOD

In this paper, detection of glaucoma in the initial stages in order to prevent vision loss by estimating cup to disc ratio using image processing. Further to automate the disease detection process deep learning algorithms are implemented. CDR value is determined after separating optic disc and cup employing image processing techniques. By using image processing the segmentation will be easier. Image processing is rapid, requires less time, advantageous and it will give fruitful results and more profitable. It does not require any chemicals to capture the images and increases the quality and removes the noise in the image required for the diagnosis of the disease. Some of the main features of the medical images requires edges which are preserved and can be used for collecting information for the medical analysis. We can get each and every pixel in the image that is needed for our analysis process. Hence, digital image processing techniques are used for our disease detection process.

Further to automate the disease detection procedure machine learning can be used. Machine learning is the process of training the model with datasets and model learns by itself during the training process and able to classify the given images as glaucoma and healthy images. Machine learning needs to extract the features manually then classification is done by the system considering the features extracted. But extracting features from the fundus image is more complex and are sensitive. Glaucoma can be detected by using other features in addition to cup to disc ratio, which are sensitive in nature to get more accurate results. So, Deep learning algorithms are implemented which is a subdivision of Machine learning. DL algorithms extract more features and then divide them as healthy and glaucomatous. Deep learning is training the model using more datasets. Since, feature extraction and classification will be done by the model itself exactly by using the training data. Convolutional neural networks are used for the extraction and classification purpose.

Glaucoma is such a chronic disease need to be detected in its earlier stages using computed CDR value. The constraint in the recognition process of glaucoma is CDR value. To calculate CDR, image processing techniques are employed and further, automate the detection process by applying it to a Deep learning model in order to include more features for classification because, the glaucoma can also be detected using other parameters to get more accurate results. After detecting whether the person is affected by glaucoma or not is pinged through mobile to patients and ophthalmologist for further treatment. Flow diagram of proposed method is illustrated in Fig 3.

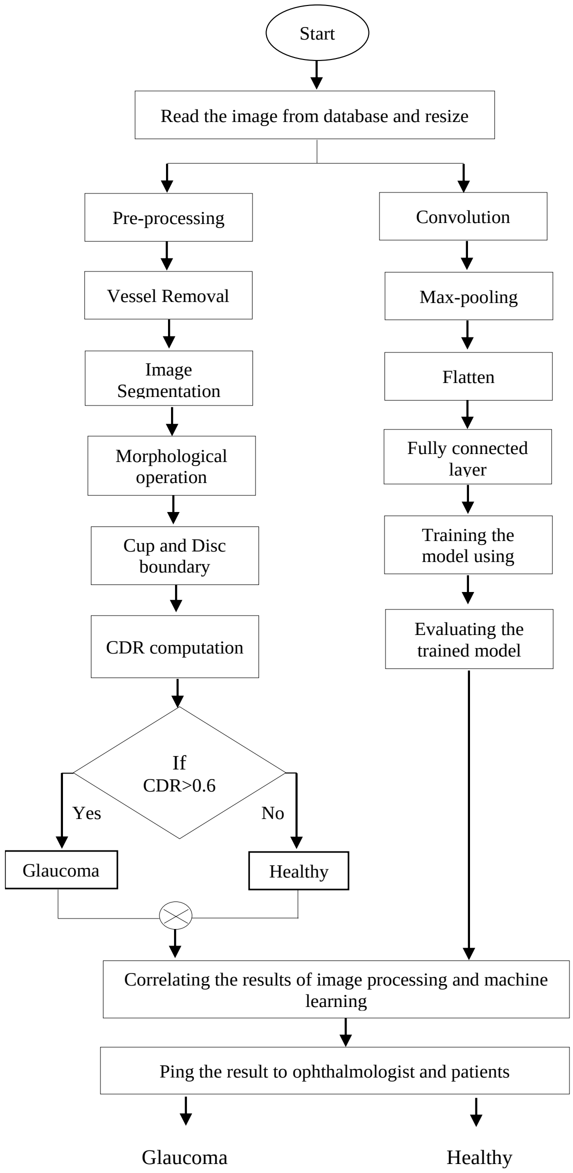


Fig 3. Flow Diagram of proposed method

A. Using Image Processing

To determine glaucoma calculation of CDR value is required. CDR is evaluated by extracting the disc and cup regions using image processing techniques. Retinal fundus image is obtained from fundus camera which captures the illumination reflected from the retinal surface. The dataset contains 30 fundus images, 15 healthy and 15 open angle glaucomatous images from 20 to 70 years people. Images acquired are pre-processed in order to enhance the performance of the image processing like Image transform, Segmentation, Feature extraction etc. and also to remove the noise which may cause problems while disease detection. Pre-processing contains resizing the images, image normalization, removal of noise.

B. Optic Disc Extraction

The higher intensity or the brightest region of the fundus image is optic disc, where rods and cones are not present often known as blind spot. The beginning of the optic nerve is optic disc. An algorithm is proposed to detect optic disc in shown in the Fig 4.

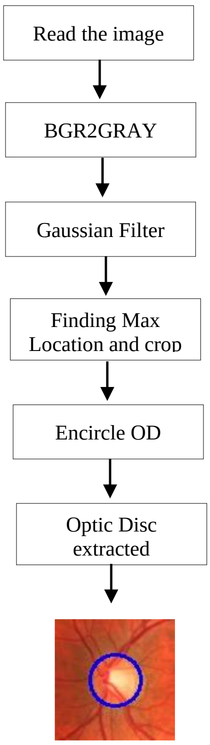


Fig 4. Optic Disc Extraction

Retinal fundus Image from the dataset is read as input randomly. Initially, images are resized to 240 x 240 required for further processing. Region of interest (ROI) is extracted prior to the pre-processing of the fundus images. ROI is the region contains the information required for the detection process. The reason behind the extraction of region of interest is to reduce the image size and also to reduce the complexity of the further tasks which are performed for detection process. The first step in the partitioning of optic disc is to extract the ROI as shown in Fig 5. To fasten the CDR calculation ROI region to be extracted accurately. ROI will be less than 11% of the Fundus image [2]. By observation we can say that optic disc region contains more brighter pixels in comparison with the other pixels of the image. Pixels at the optic disc center has highest intensity. Boundary of ROI is double the diameter of the optic disc, used to segment optic disc and cup. By extracting the region of interest, it is easy to segment required region.

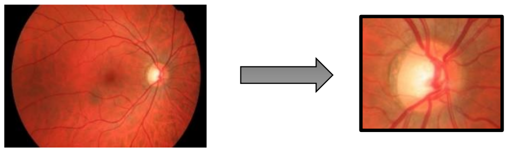
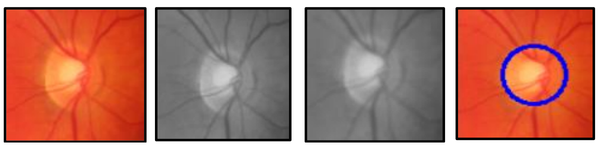


Fig 5. ROI extracted

BGR system of colors used for computer display. BGR images are converted to grayscale as grayscale images are easier for further processing because grayscale images contain only the darkest shade is black and the lightest shade is white. Since grayscale contains only two colors black and white it is easy to detect the higher intensity and lower intensity pixels easily. Gray image is fed as input to the gaussian filter. Gaussian blur is a linear filter, which is also called as gaussian smoothing, which performs the blurring operation so that noise can be reduced. Image blurring will be done by Gaussian function as shown in (1).

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{1}$$

where, x and y are the horizontal and vertical distance from origin respectively and σ is the standard deviation of the gaussian function. To find the max location Minmax function is used, which outputs the minimum and maximum intensities of the image along with the location of the minimum and maximum intensities. The computation of finding maximum intensities is carried on by finding out one highest intensity pixel later by updating each pixel by comparing with the neighboring pixels in the ROI. By observation we know that higher intensity is nearer to the optic disc and cup. So, by localizing the higher intensity pixels along with the position of the pixels and then shape fitting on the optic disc.



(a) (b) (c) (d)

Fig 6. Steps to extract Optic-Disc; (a) ROI, (b) Grayscale, (c) Gaussian Blur, (d) Encircle OD

C. *Optic Cup Extraction*

Optic disc has white cup like area called optic cup. Fig 7 illustrates the optic cup extraction. RGB image is read and then region of interest is cropped as per the concept of max intensity location. To segment the cup region inside optic disc (OD), Pixels of the green channel are more prominent since they have more contrast, visibility and brightness.

Image is split into R, G, B channels. Closing operation is performed in order to fill the boundary pixels of image by applying dilation followed by erosion. Enhancing the contrast of the fundus image using stretching operation, by replacing the certain intensity pixel values to a preferred intensity value. Initially if any image has to be normalized, we have to specify the lower and higher pixels values. These limits will act as minimum and maximum pixel values. The limits can be calculated using the equation (2),

$$P_{out} = (P_{in} - c)\left(\frac{b-a}{d-c}\right) + a \qquad (2)$$

If the values are less than 0 are replaced by 0 and greater than 255 are replaced by 255. Mainly contrast stretching is applied to visualize the optic cup prominently. In RGB, separation of color information from luminance is not possible. Hence using HSV we can separate image color information from luminance. 'Hue' represents color, 'saturation' represents how much of amount of color is added is with white, 'value' represents how much of amount of color is added with black. Median filtering is applied on the saturation channel which removes the noise where Optic cup region is more prominent in S channel. Median filter replaces all the pixels by the median value calculated for further cup extraction. Color enhancement is done in order to improve the contrast for better segmentation of cup region. LAB color space is formed by converting HSV image to enhance the color space of the cup region for segmentation.

An unsupervised iterative technique called k-means clustering, has n number of observations are classified as k number of clusters. Centers for k clusters are chosen randomly. Allocating each pixel to the cluster as it reduces the distance from the centers. For the reduction of noise in the clusters by applying it to a bilateral filtering to preserve edges. To detect the optic cup edges by suppressing noise by applying canny edge detector to the bilateral filtered image. Contour is used for combining all the points along the boundary containing same intensity pixels for object detection and analyzing the shape of the object. Boundaries are smoothened using linear ellipse fitting, after extracting the edges. To fit an ellipse Least square fitting algorithm is used which smoothens the edges after detecting edges using canny edge detectors. After fitting an ellipse to the optic cup, optic cup will be extracted.

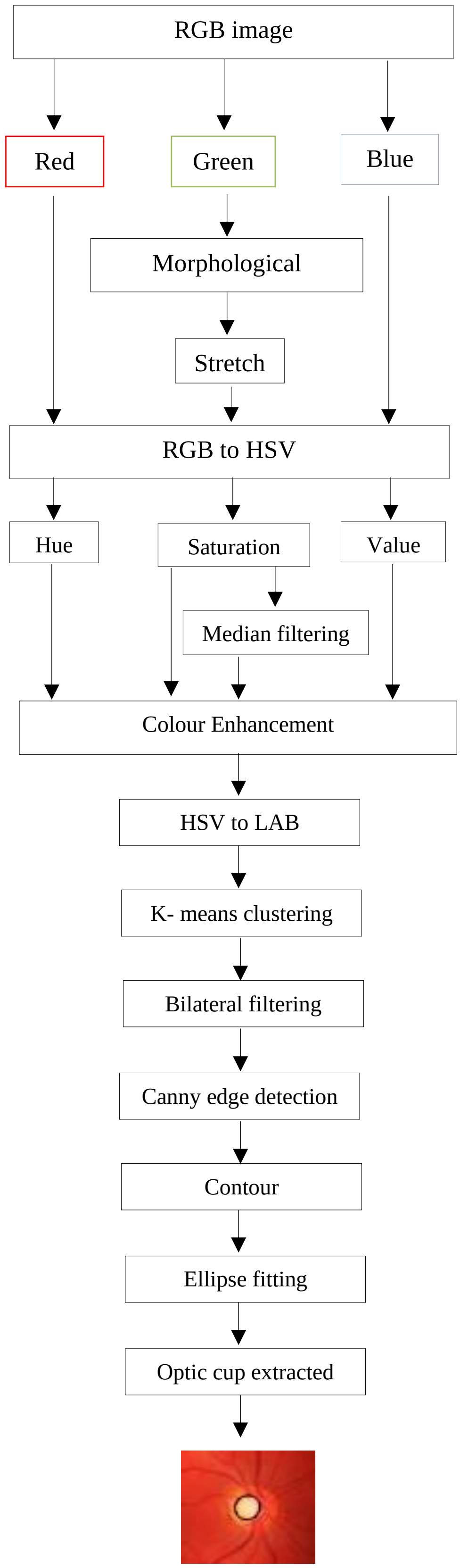


Fig 7. Optic-Cup Extraction

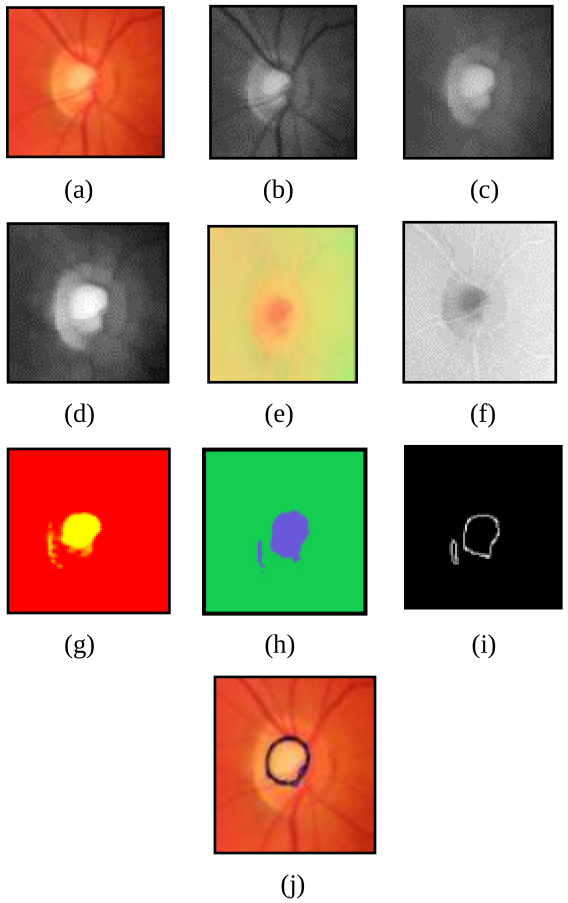


Fig 8. Steps to extract Optic-Cup; (a) ROI Image, (b) Green channel, (c) Morphological operation, (d) Stretching, (e) RGB to HSV, (f) Saturation channel, (g) Colour enhancement, (h) K-means Clustering (i) Canny Edge and (j) Ellipse fitting

After extracting optic cup and disc, estimate cup to disc ratio to categorize the images as glaucomatous or normal. CDR can be calculated as,

$$CDR = \frac{Area\ of\ Cup}{Area\ of\ Disc} \quad (3)$$

For a normal retinal image CDR will be less than 0.5, if it exceeds this range, image will be classified as glaucomatous image.

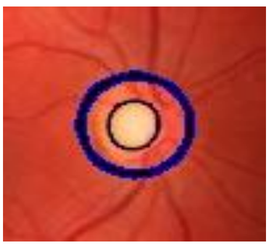


Fig 9. Optic-Cup and Optic-Disc

D. Using Deep Learning

Deep learning is a subset of machine learning that train with the Large number of labelled datasets. It may be supervised, unsupervised or semi supervised learning. Deep learning mainly used to extract the features in the higher layers. Normal neural network has 2 - 3 hidden layers but more than 150 layers are present in deep neural network. CNN are the most important type of deep neural networks mainly used for images. So, for disease detection process we are implementing our model using CNN.

In our proposed method we implemented two deep learning models, one is sequential model using CNN and other is VGG19 model. VGG19 is a pretrained deep convolutional network. Later comparison is made between the two models. These two models are trained for certain number of epochs until best results are achieved. Sequential model is one of the types of convolutional neural networks. It assembles the convolutional neural layers sequentially. The four layers of the sequential model are; convolution layer, Maxpooling layer, Dense (Fully connected layer) and Non-linear layer, by these series of layers, features in the higher layers are extracted. CNN can be implemented using keras models. The process of extraction and classification of the given dataset is given in the Fig 10.

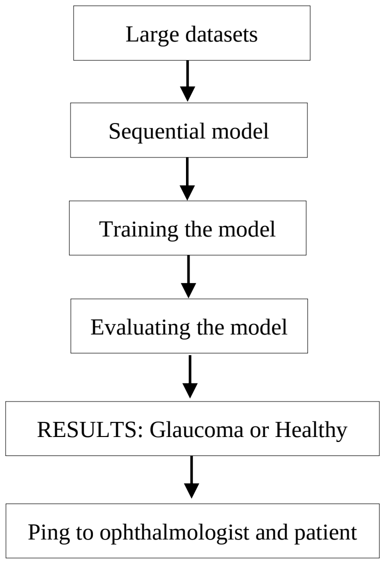


Fig 10. Implementation of Sequential Model

The dataset contains 1640 fundus images: 700 normal and 690 glaucomatous images for training, 80 normal and 70 glaucoma images for validation and 50 normal and 50 glaucoma images for testing. The images are resized to 240 x 240 pixels. Sequential model is a type of keras. Initially the model needs to know the shape of the input image. Later image is given to convolutional neural networks. Patterns of the images are extracted from the four layers of CNNs. Features are extracted in the convolution and maxpooling layer and the classification will be done in the fully connected layer. Convolution layer mainly consist of two parameters; one is filter size and second is filter count. These filters(kernels) are used to extract the features. Here we have used two convolutional layers, first layer extracts the features like lines, edges, corners. The other operations in convolution layer is sliding. Sliding operation will be operated on the input 2D image beginning from the top left corner to bottom right corner, during these sliding processes, each pixel gets multiplied with the kernel to perform convolution operation. To create feature maps of the output pixels, each pixel from the input 2D is multiplied with the kernel and stored in the feature maps and these features will be input to the next layers. The input to convolution layer with image size of 28x28 with filter size 5x5, then the first hidden layer will be of size 24x24. It will be calculated as (N-k+1) (N-K+1) where N and K represents the input image size and filter size respectively.

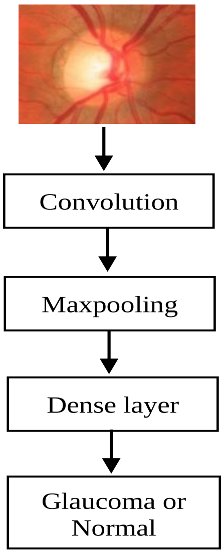


Fig 11. Classification process in Deep Learning

Maxpooling layer is added to decrease the difficulty in the feature extraction by giving more importance to the features which having maximum weightage in the given window size. Normally the stride size will be the window size. Feature will be extracted using the two layers convolution and maxpooling layer. Later classification will be done by corresponding layers. Fully connected layers expect the input to be 1D. But the output of convolution and maxpooling layer is 3D. Hence flatten is used to convert the output from 3D to 1D. Non-linear layer is utilized to make the output layer non-linear; activation function is used as one of the parameters in the convolutional layer. Here activation function ReLU is adopted.

ReLU function will be implemented using y = max(x,0). which replaces the negative values with zero and positive values will be kept as it is. Fully connected layer is the output layer also known as Dense layer. Output from the maxpooling layer is 3D, converting 3D to 1D is done by flatten layer in order to fasten the processing. All the outputs from the previous layers are given to dense layer as an input and they are classified as Glaucoma or healthy. Now, for compiling the model and training purpose CPU or GPU are used. Some other parameters also we need to specify like loss function, accuracy etc. optimizer is used to evaluate the weights and reporting and collecting the information obtained during the training process. Loss argument is defined using binary-cross entropy. “Adam” is the optimizer used, which updates a model using training dataset. Accuracy of the classification model will be calculated using “metrics” argument. Activation function used in the output layer is Sigmoid. It is implemented to classify the given data as either 0 or 1. sigmoid function is going to classify the data to glaucoma or healthy image. It is a Non- linear activation function. This function can be implemented using the formula given below:

$$\phi = \frac{1}{1+e^{-Z}} \tag{4}$$

Training the model is to choose the weights to the inputs to get expected output. Deep learning model needs large dataset if we have few data set then there is alternative to this case is Image data augmentation. It is the process of increasing the dataset by performing some minor operations on the existing datasets like mirror images, rotating the image certain amount etc.so this leads to the expansion of our dataset which increases the performance and accuracy of the model. Training is carried on certain number of epochs and each epoch gets split into batches. Batch size and number of epochs are defined using batch-size and epochs arguments. Our model will be trained for chosen number of batch size and epochs. Evaluating the trained model to calculate the performance of the model. Inputs will be given to the model which predict the outputs. Collecting the information of predicted outputs will give the loss and accuracy of the model. The model is trained for certain number of epochs to get the best accurate results. After evaluating the trained model, we can test our model for different test image. It will give the result as whether the given fundus image is affected by glaucoma or not.

VGG is one of the deep convolutional neural networks. Similar to the sequential model VGG19 also contains Convolutional layers like convolution layer, maxpooling layer, non-linear and fully connected layer. and training on a pre-trained model that is VGG19. There are 16 convolution layers and 3 Dense layers in VGG19 model. For training this pre-trained model consumes more time because of a greater number of convolution layers and training will be very slow during the first time of training. Non-linear layer ReLU (Rectified Linear Unit) is used and another activation function SoftMax is utilized in the last layer of the fully connected layer (Dense). Since it is a pre-trained model multiclass image classification is implemented using the activation function SoftMax for predicting, the image as glaucomatous or healthy image. Stochastic gradient descent algorithm is used as optimizer and implemented using “Adam” as optimizer.

"Categorical-Cross entropy" is used as the loss argument. metrics argument is used to calculate the accuracy. In this way model is developed using VGG19 pre-trained model.

IV. GUI IMPLEMENTATION

After successfully accomplishing the detection process using image processing and deep learning, further in order to make it user friendly, we are implementing on graphical user interface (GUI). The GUI system is shown in the Fig 12.

Fig 12. GUI window for Glaucoma Detection

The system after loading the retinal fundus image from the local directory by pressing the select image button as shown in the Fig 13. Later image which is selected is converted into Gray scale for further processing is shown in the Fig 14.

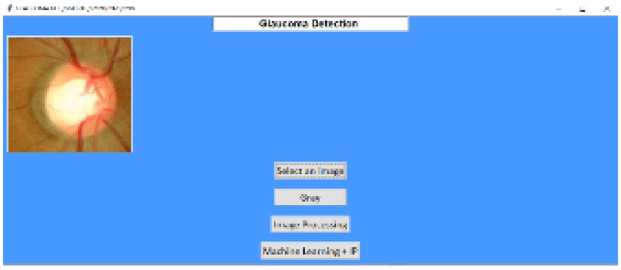


Fig 13. Loading an Image

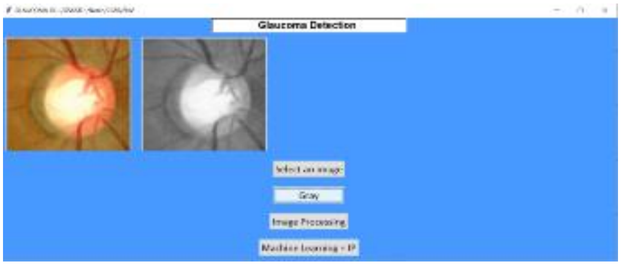


Fig 14. GUI after converting RGB image to Gray

The system will calculate cup to disc ratio after converting the image to grayscale and extracting the region of interest using image processing and displaying the areas of optic disc and cup and including cup to disc ratio. Depending upon the cup to disc ratio, the system will give the results as glaucoma or healthy. Detected optic disc and cup is given in the Fig 15.

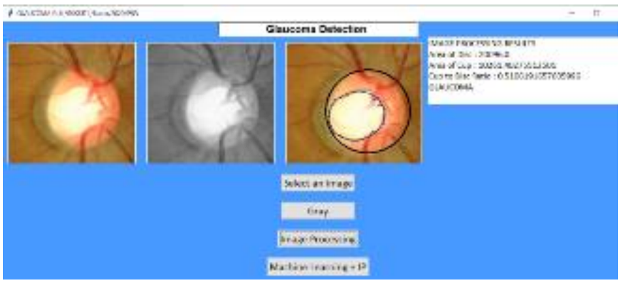


Fig 15. Image Processing Result

After classifying the image as glaucomatous or healthy using Image processing techniques, now in order to detect the disease effectively and also to include other features of fundus image, deep learning algorithms are employed. Correlating the results of both the techniques of image processing and deep learning in the detection process and the results are displayed on the GUI as shown in the Fig 16.

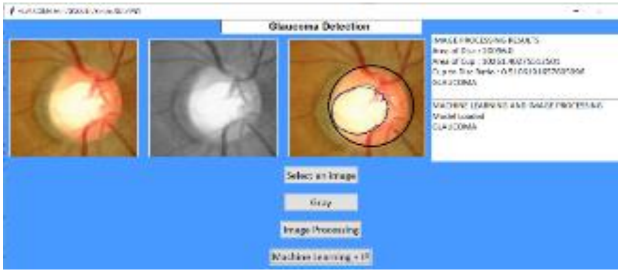
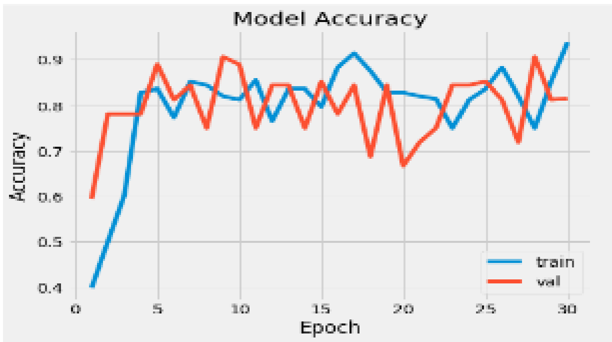


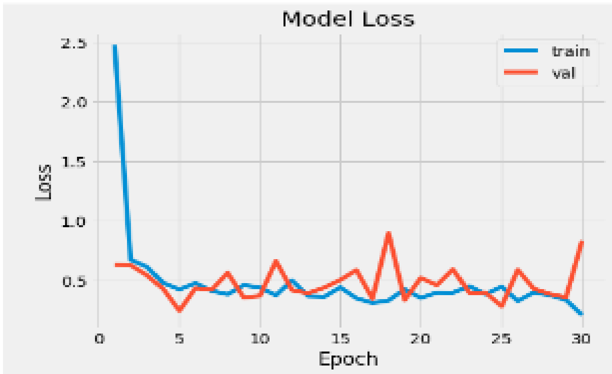
Fig 16. Final Result based on Image processing and Deep Learning

V. RESULTS

We successfully accomplish the detection of open angle glaucoma in the early stages efficiently using image processing and deep learning for retinal fundus images. In image processing, 30 fundus images are used, 15 glaucomatous and 15 healthy images. By extracting the disc and cup region, CDR value will be estimated if CDR is more than 0.5 then person is affected by glaucoma and the results are pinged to both patient and ophthalmologist for further treatment. Not only CDR, glaucoma can be detected using other parameters also like position of the blood vessels, neuro retinal rim. In order to extract those features we implemented deep learning algorithms. Mainly for image classification, convolution neural network is used. Two CNN models are implemented, sequential model and VGG19 model to segregate the given retinal image as glaucoma and healthy image. Dataset contains 1640 retinal fundus images. 700 healthy and 690 glaucomatous images are used for training 80 healthy and 70 glaucoma images for validation and 50 healthy and 50 glaucoma images for testing purpose. Accuracy of both the models are calculated in order to check the feasibility of the models. Fig 17 (a) and (b) shows the graphical representation of accuracy and loss of sequential model. Accuracy achieved by the sequential model is 84.51% with a loss of 0.620. Accuracy achieved by the VGG19 model is 80% with a loss of 0.77 which is shown in Fig 18 (a) and (b). The blue curve represents the accuracy achieved during the model training represented in Fig 17 (a) and the orange curve represents the accuracy achieved during model testing which shows how well the model has been trained to classify the data. In Fig 17. (b) blue curve represents the number of images failed in recognizing as glaucomatous or healthy image. Similarly, Fig 18. (a) and (b) represents the accuracy model and loss model of VGG19 model. All the simulations are done on the Spyder IDE using OpenCV Python.

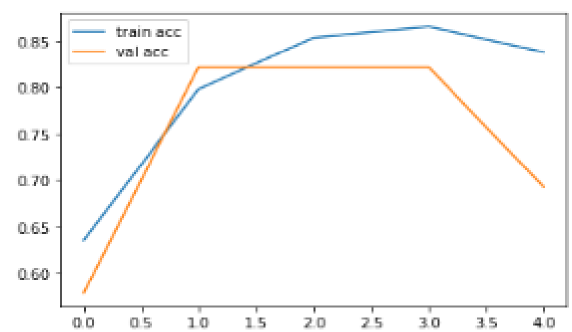


(a)

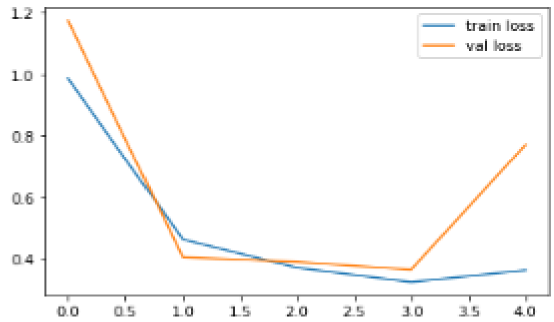


(b)

Fig 17. Graphical Representation of Accuracy and Loss Models of Sequential Model; (a) Accuracy Model; (b) Loss Model



(a)



(b)

Fig 18. Graphical Representation of Accuracy and Loss Models of VGG19 Model; (a) Accuracy Model; (b) Loss Model

Both the CNN models, Sequential model and VGG19 model are able to classify the given retinal fundus images as glaucomatous image and healthy image. But the accuracy of the sequential model is more compared to the VGG19 model in glaucoma detection and also VGG19 is pretrained model. Since VGG19 is a pretrained model the weights are also pre trained and these weights are used for this problem also. But for each problem it requires different weights because of different dataset. But in case of sequential model weights will be calculated differently for different problem statements. So Sequential model yields better results compared to the VGG19 model.

VI. CONCLUSION AND FUTURE WORK

Glaucoma is optic nerve disease caused due the increased intraocular pressure which leads to complete vision loss if it is not detected in the initial stages. Thus, detection of disease in the early stages is necessary. Here we accomplish the detection process in the early stages using image processing techniques considering CDR value and by automating the detection using process using deep learning algorithms by extracting other features of the fundus image and achieved an accuracy of 84.51%. Later, Correlating the results of image processing and deep learning to make the system efficient. This technique gives a best solution compared to the currently existing technologies as they need plenty of time to detect the disease and expensive. This disease detection process will assist the ophthalmologist to treat the glaucoma affected patients more accurately and also results are pinged to patients and ophthalmologist. This disease detection can be extended for other eye related diseases like, Age-related macular degeneration (AMD), diabetic retinopathy etc. Fundus camera can be developed to capture the fundus images.

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