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Glaucoma Detection Using Machine Learning Algorithms

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Abstract : GLAUCOMA is an irreversible and incurable eye infection in which the optic nerve is consistently hurt. It leads to slow progressive degeneration of the retina. Though it can not be fully cured, the progression can be controlled by detection in the early stage. Glaucoma affects the Optic Head Nerve and its density is dependent on measurement of Optic Cup and Optic Disc. We can develop a model in which glaucoma can be recognized/detected in the starting period only so that further loss of vision can be prevented. We can use different algorithms like CNN, logistic regression, K- nearest neighbors classifier, Support Vector machines. All these techniques can be used to measure OC and OD dimension. We are planning to use different datasets like ARIA, RIGA and will be using FUNDUS images which later will be converted into segmented images. Our aim will be to provide a comprehensive overview of various machine learning algorithms which are used to detect GLAUCOMA based on fundus images and finding out the best algorithm which gives the best accuracy

***IndexTerms* – Glaucoma, Intraocular Pressure(IoP), ResNet, LAG, ARIA, VGG.**

I. INTRODUCTION

A. What is Glaucoma

Glaucoma is a complex ocular disease in which the optic nerve is damaged,it can cause progressive,irreversible vision loss . Glaucoma causes vision loss which begins from the peripheral regions and in certain cases it leads to a permanent vision loss. The World Health Organisation (WHO) says that Glaucoma is the second foremost cause of blindness worldwide. Most of the times the optic nerve is damaged because of the increased pressure in the eye. This is known as intraocular pressure. The origin of the word Glaucoma can be dated back to the Byzantine and Greek eras as far as 762 B.C , first seen in the works of homer who described it as ‘sparkling silver glare’ then Hippocrates in 400 B.C used the term ‘glaucosis’ to describe the conditions that correlate with dimming of the vision. Later in 1662 , A British Ophthalmologist Richard Banister provided the first clear description of glaucoma and furthermore he established the connection between increased tension of eyeball and glaucoma.

Healthy eyes

Periphial vision loss due to glaucoma

(1)Comparison between a Healthy eye and a Glaucoma eye

As seen in the figure an eye infected with glaucoma suffers from a peripheral vision loss.

B. Causes of Glaucoma

A. High Pressure in the eye- the intraocular pressure: Aqueous humor liquid leaves the eye through cornea and iris. If the channels of cornea and iris are blocked or partially obstructed, intraocular pressure(IOP) in our eye may increase.When intraocular(IOP) increases, the eye's optic nerve may be damaged.

B. Different reasons to increase Pressure in the eye:

i. Dilating eye drops
ii. Blocked or restricted drainage in the eye
iii. Poor or reduced blood flow to the optic nerve

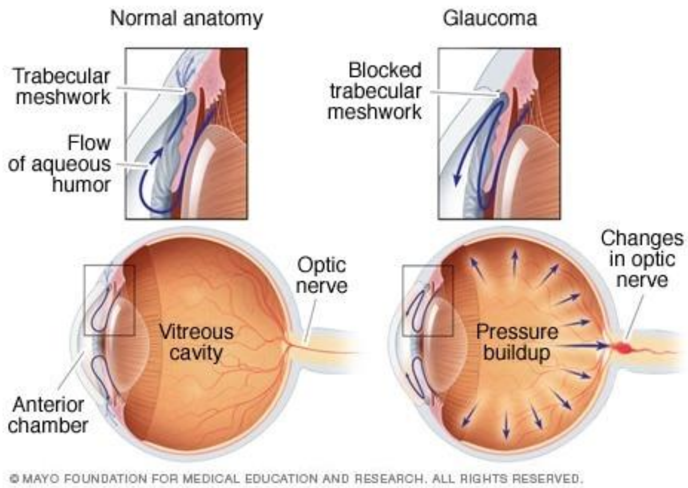

Fig. 2: Intraocular Pressure (IOP)

C. Family history of glaucoma:

D. Eye fluid unable to flow properly: The back of our eye continuously makes aqueous humor liquid and the front part

II. of the eye is filled up with this liquid. If there is a failure of the eye to maintain balance between the amount of internal eye fluid produced and the amount of fluid drained away. As aqueous humor is produced behind the iris, it flows into the anterior chamber through the pupil. Too much aqueous production or obstruction of outflow can cause rise in IOP and eventually glaucoma.

E. Inflammation within the eye:

F.Extra pigment being dispersed within the eye:

G)Medical conditions like diabetes and high blood pressure: Diabetic retinopathy, the most common form of diabetic eye disease and a consequence of diabetes, can raise your risk of glaucoma. People who have had diabetes for a long period are more likely to develop diabetic retinopathy. This condition's risk rises as follows: Age Blood pressure that is too high Uncontrolled blood sugar High blood pressure causes higher eye pressure, probably because it increases the amount of fluid produced by the eye and/or alters the drainage mechanism of the eye.

C. Categories Of Glaucoma

Glaucoma can be of different types. The two main types: Open-angle Glaucoma and angle-closure Glaucoma. These are caused due to rise in intraocular pressure (IOP), i.e The pressure inside the eye.

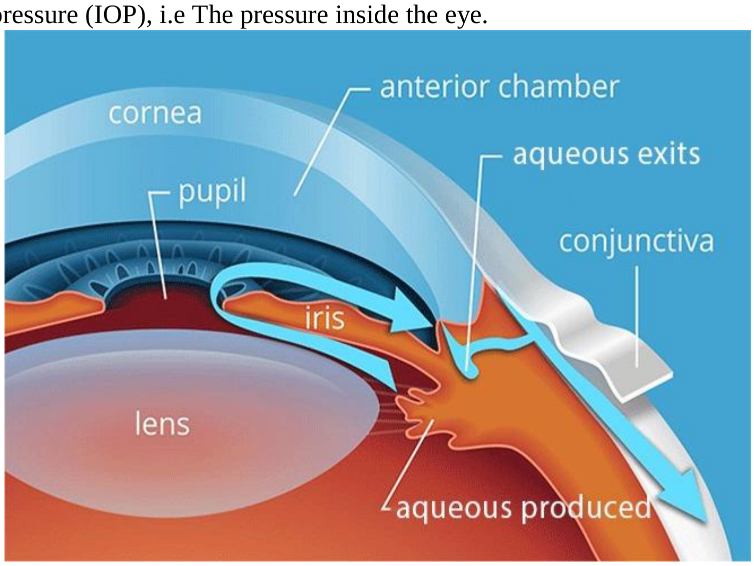

Fig. 3: Human Eye's Anatomy

1) Open-angle Glaucoma: Open-angle Glaucoma is most common types which is 90 percent patients have. It is also known as Primary or Chronic Glaucoma. "Open-angle" refers to the angle where the cornea meets the iris and it is as wide and as open.

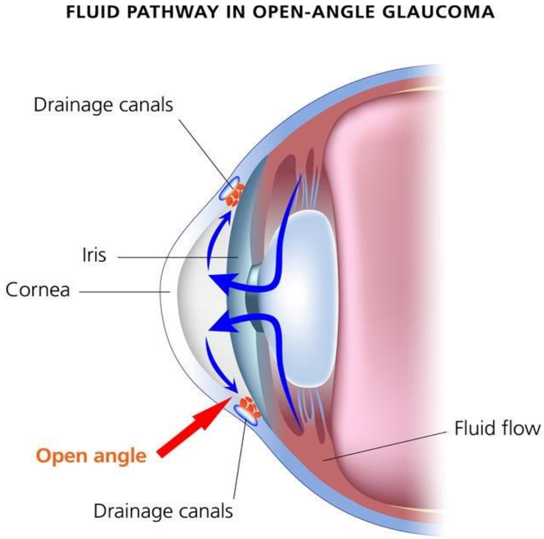

Fig. 4 ; Open Angle Glaucoma

2) Angle-Closure Glaucoma: This type of glaucoma is a rarer occurence of glaucoma. It is also reffered to as Acute or Narrow-angle Glaucoma. On the contrary of Open-angle Glaucoma, angle-closure glaucoma means the angle between the iris and cornea is closing.

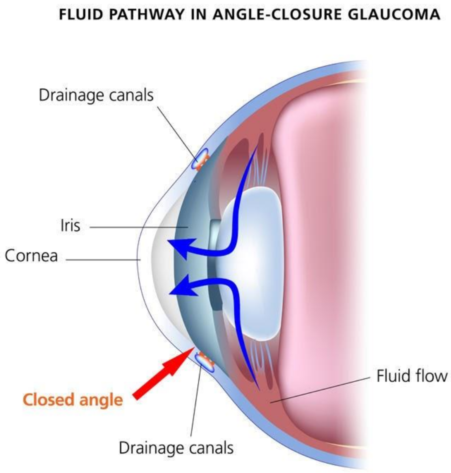

Fig. 5: Angle Closure Glaucoma

Table 1
DIFFERENCE BETWEEN OPEN ANGLE AND ANGLE-CLOSURE GLAUCOMA

Sr. No.	Open angle Glaucoma	Closed Angle Glaucoma
1	It is mainly caused by the slow clogging of the drainage canals, hence finally resulting in increased eye pressure.	It is mainly caused by blocked drainage canals, hence resulting in a sudden rise in intraocular pressure.
2	It consists of a wide and open angle that the iris makes with cornea	It consists of a closed or narrow angle that the iris makes with cornea cornea.
3	It generally increases slowly and is a lifelong condition.	It develops quickly and rapidly
4	The damages created are not noticed quickly	The damages made are noticeable effectively over the period

D. Fundus Images

Fundus means part of a hollow organ that is furthest from the opening. In the case of the eye the fundus is the posterior membrane of the eyeball which consists of retina, macula, fovea, posterior pole and optic disc. Ophthalmologists manually check the fundus of patients using an ophthalmoscope which is called fundoscopy. Optical Coherence tomography is the technique used for obtaining the fundus images of the eye which then can be used for detection and prediction of glaucoma disease. In Fundus images we can identify the optic disc as a region of bright concentric circles of different brightness. The inner bright circle forms the optic cup and outer circle forms the optic disc and the region between the two forms the neuroretinal rim. Out of the structural and functional features used for glaucoma detection, CDR (Cup to Disc Ratio) is found to be most important. CDR can be calculated as (Area of Optic cup / Area of Optic disc).

CDR = Area(Optic cup) / Area(Optic disc)

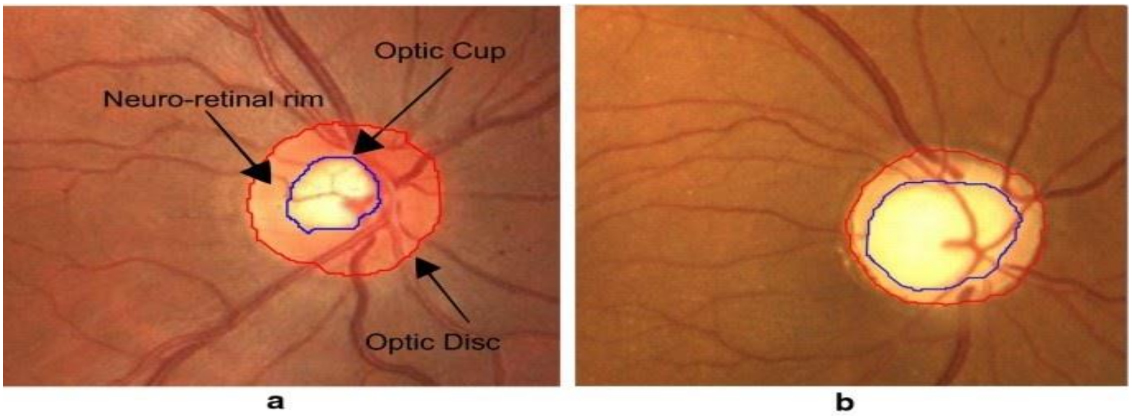

Fig. 6: normal eye image(a) and glaucomatous eye image(b)

2. Literature Survey

A. SVM(Support Vector Machine):

support-vector machines are supervised machine learning models which analyze data and separate and retrieve analysis. It is used to solve both types of split and back problems. In SVM, segregation is done by finding the HYPER-PLANE which divides the classes very well. It is a discriminatory category officially formulated by dividing the hyperplane. It is a representation of examples such as the points in the space drawn on the map so that the points of the different categories are separated by a wide gap as possible.

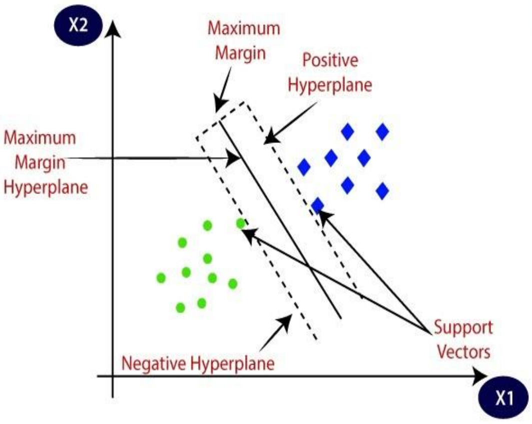

Fig. 7: Support Vector machine

1) Hyperplane: It is mostly a decision plane which distinguishes the group of objects that belong to different classes.
2) Margin: Margin is a gap between the two lines on the closest class points. This is calculated as the shortest distance from the line to the closest point or the support vectors. If the margin between the classes is bigger, then it is regarded as a good margin, a smaller margin is not a good margin.
3) SVM Kernel: SVM is implemented using a SVM Kernel. It transforms input data into required format. Kernel takes low-dimensional input and converts it into high dimensional (with more features) output. To put it another way, it converts inseparable problem to a separable problem by adding more dimensions to it. It is most useful in non-linear separation problem. Kernel trick assists you to build a better classifier.

a) Types of Kernel:

Linear Kernel- It can be used as the normal dot product of two observations.

$$K(x, xi) = sum(x * xi)$$

Polynomial Kernel- It is said to be the more standardized form of linear kernel. It can distinguish nonlinear or curved space.

$$K(x, xi) = 1 + sum(x * xi)d$$

Fig.3 Fig.4

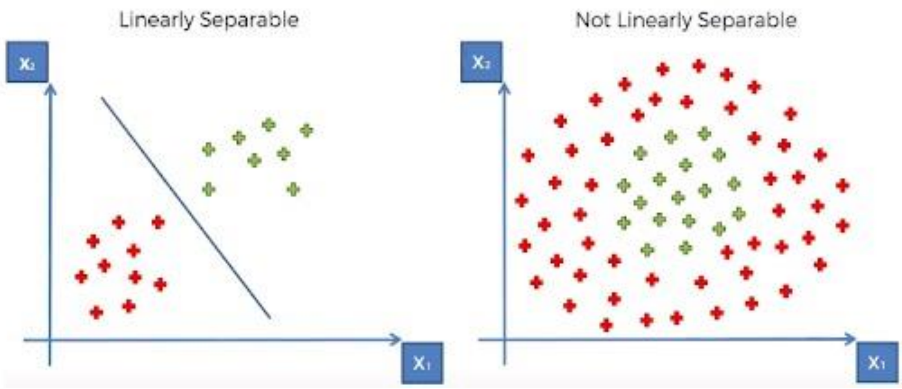

Fig. 8: SVM kernel types

M.Shanmuga Eswari et [2] proposed using patients' health records for predicting the possibility of a patient getting glaucoma. The health record contained data such as blood pressure, visual acuity, blood sugar, hypertension, age, family history, etc. Classification was done using BOSVM, LSVM, MGSVM out of which results given by BOSVM were more accurate. It is hard to find such datasets.

It is hard to find such datasets.

B.CNN(Convolutional Neural Networks)

Artificial Neural Networks are utilised for a variety of classification tasks, including picture, audio, and word cate gorization. Different types of Neural Networks are used for a wide range of purposes, including We employ Recurrent Neural Networks, which are more precise than LSTMs, to forecast the sequence of words, and Convolution Neural Net works for image categorization. Among other characteristics, convolutional neural networks (CNNs) are well-known for their capacity to learn quickly. discriminative features from raw pixel intensities. The ability of CNN designs to extract
information is what gives them their power, highly discrimi nating features at multiple levels of abstraction.

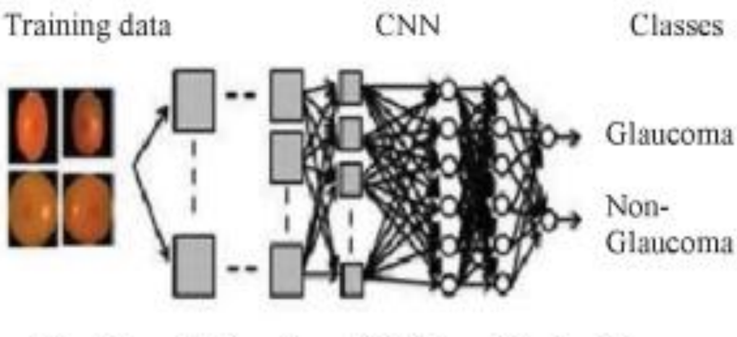

Fig. 9: Convolutional Model

Arkaja Saxena et [?] proposed a six layer model out of which the first four were convolutional layers and the last two layers were fully connected. CNN layers were used to learn the features of the fundus images. On performing classification on ORIGA and SCES dataset the proposed method gave substantially good results as compared to State of the art method.

Manar Aljazaeri et al [4] proposed a two step model for classification of retinal fundus images. MESSIDOR and Magrabi datasets were used. First step involved identifying the optical disc region of the fundus image using RCNN which was followed by the second step in which a regression network was trained to calculate the CDR. Faster RCNN act as main component for the feature detection step, after that a network for region proposal having 2 head branches, first used for bounding box regression and second used for classification, the remaining branch of Mask RCNN employs the region of interest provided from region proposal network as input to next dense convolutional network for determining mask region of the predicted region of interest. In the proposed method DenseNet acts as a regressor which takes input from the RCNN detector and subsequently using regression loss the model is trained. Now the output obtained and having dimensions (8 X 8 X 1664) is used and kept on a global averaging layer and then a dense convolutional layer of size 1 is added and using adam optimizer trained over a hundred cycles. 70 percent of the MESSIDOR dataset was used for training purposes and the whole Magrabi and remaining 30 percent of the MESSIDOR dataset was used for testing purposes. Optical Disc accuracy for MESSIDOR dataset was 100 percent while for Magrabi dataset it was 98 percent.

Table II
Results of RCNN and DENSENET model

Datasets	MESSIDOR Dataset	Magrabi Dataset
Proposed Model	Mean Square Error =0.0008 Mean Absolute Error = 0.023	Mean Square Error =0.0098 Mean Absolute Error = 0.053
Standard UNet Model	Mean Square Error =0.025 Mean Absolute Error = 0.088	Mean Square Error =0.014 Mean AbsoluteError = 0.095

The model performed better than the UNet models. RCNN algorithm for CDR calculation and then Dense Convolutional network algorithm for classification gives better performance rather than regular segmentation and then calculating CDR.

C. ResNet (Residual Network)

The word 'Residual Network' is abbreviated as Resnet. ResNet is a Neural Network type that was first described in the paper "Deep Residual Learning for Image Recognition" published in 2015. Jian Sun, Kaiming He, Shaoqing Ren and Xiangyu Zhang are the authors of this work. ResNet, or residual networks, were introduced to help relieve the problem of training extremely deep neural nets. Resnets are made up of 'Residual Blocks'.

ResNet's implementation is inspired by VGG-19's 34 layer architecture of plain network, in which shortcut connections are added between certain layers. As seen in the diagram below, these shortcut connections are what change the design into a residual network. Amer Sallam et al [1] presented a feature extraction model based on transfer learning. LAG (large scale attention based glaucoma) dataset was used. To adapt the pre-trained models for glaucoma dataset changes in the last (classification) layer were done. Alexnet, VGG-11, VGG-16, VGG-11, VGG-16, VGG19, The Googlenet(inception V1) and a few ResNets viz. The ResNet-50, ResNet-101, ResNet - 152 and ResNet – 18 Of the listed transfer learning models precision, accuracy and recall performance parameters were highest for ResNet-152 on the given dataset. Using transfer learning techniques the need for huge datasets for deep learning models was overcome.

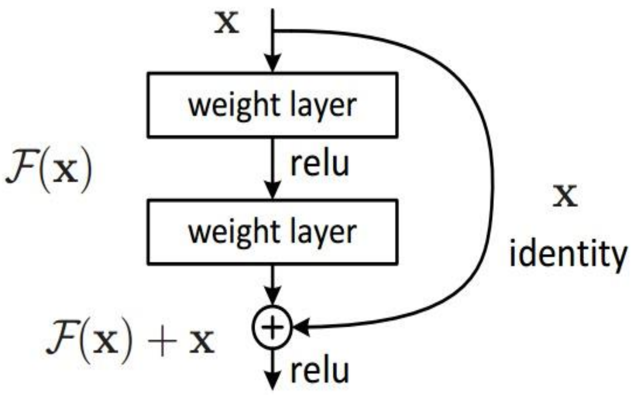

Fig. 10: Residual Network

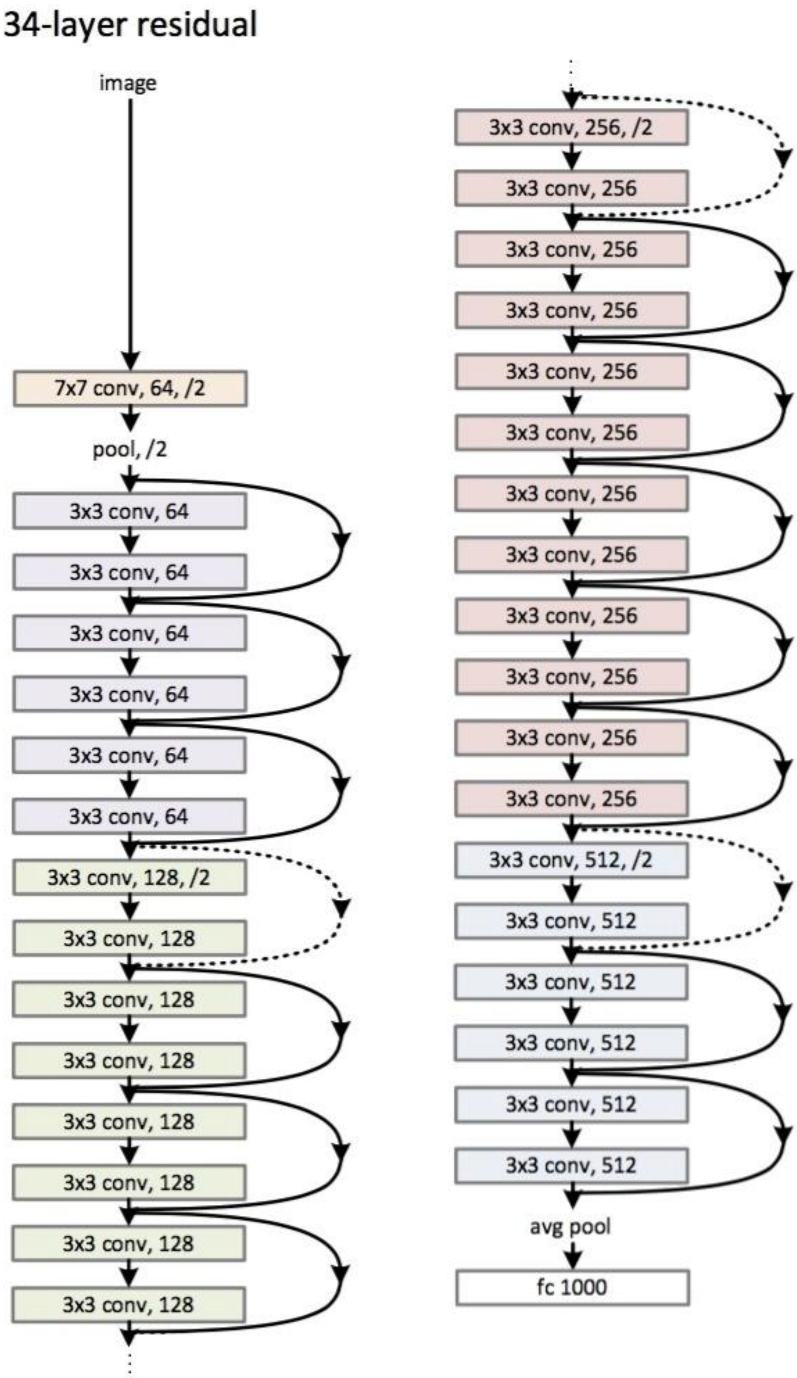

Fig. 11: Structure of Residual Network

D. VGG-16(Visual Geometry Group)

VGG-16 was proposed by K. Simonyan and A. Zisserman from Oxford University. It is a Convolutional Neural Network (CNN) model. It was proposed in "Very Deep Convolutional Networks for Large-Scale Image Recognition" research paper. It gives 92.5 percent accuracy on the ImageNet dataset which consists of 14,000,000 images and over 1000 classes. The above figure shows the architecture of VGG-16. Its improvement over the AlexNet model is that it uses multiple 3*3 kernel-sized filters one after another instead of large kernel-sized (5 in second layer and 11 in first layer) filters used in AlexNet. Due to its depth and densely connected layers it takes a very large amount of computing resources, time and datasets to train. Hence various libraries such as tensorflow, keras provide pretrained VGG-16 models which can be then locally trained and fine tuned on specific datasets. Anuradha Panday et al [9] used global thresholding for extracting following features from fundus images: optic disc radius, optic cup radius and intern CDR(cup to disc ratio). Images from different datasets available online were used. These extracted features were used as input for the following classification models SVM, LDA, KNN, Decision Tree, VGG- 16. KNN and VGG-16 models gave outstanding accuracy of 98.

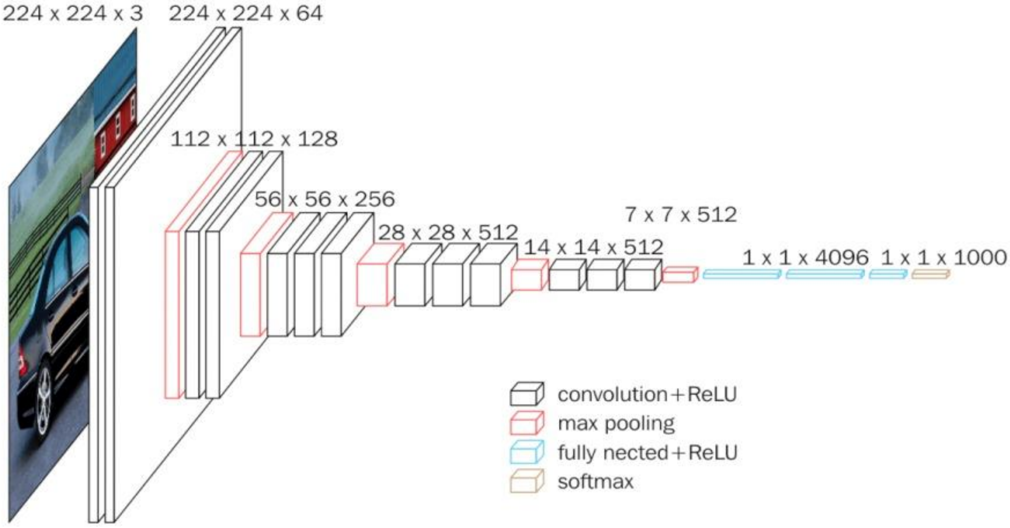

Fig. 12: Structure of VGG

E. Efficient Net

It is a rethinking model for scaling convolutional neural network models. The convolutional neural network can be scaled in three different dimensions: depth, width and clarity. Network depth depends on the number of network layers. Width is associated with the number of neurons in the layer or more precisely, the number of filters in the convolution layer. Resolution is the length and width of the given image. The image below, gives a clear idea of the scaling in all 3 dimensions.

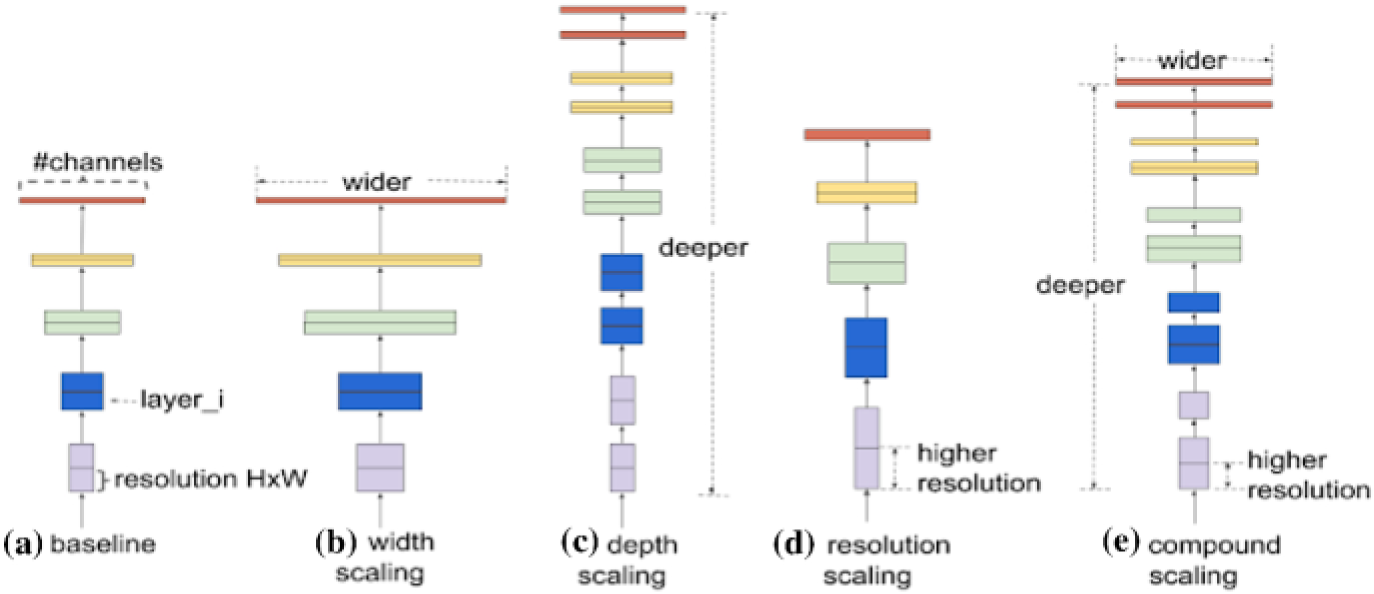

Fig. 13: Comparing different scaling techniques. Unlike the conventional scaling techniques that measure a single network size, this integrated scaling system scales equally across all dimensions.

Ana-maria Stefan et al [10] provided a brief overview of the various glaucoma detection techniques. For classifying fundus images, the primary methodologies are feature extractionbased machine learning methods, deep learning, and transfer learning techniques. First class of techniques involves identifying region of interest followed by feature extraction which is followed by classification using extracted features. The second class of techniques directly utilize deep learning and transfer learning models for classification. Methods in second class gave superior results as compared to 80 percent of the previous works done. De La Fuente-Arriaga et. al. [7] identified glaucoma using values calculated for vessel displacement using growth of holes in OD and OC. Acharya et. al. [8] presented glaucoma detection using fundus images... Here, an adaptive histogram was initially used to remove noise while also improving image contrast. Each pixel is compared to its neighbouring pixel to create a binary image, which is then used to generate values to indicate the existence of glaucoma using sequential forward search. Data augmentation is used initially on the training data to amplify the number of samples in the training data . After that, the backward and forward propagation techniques are used to train the transfer learning model. Convolutional layers with numerous filters extract forward propagation characteristics. To update the weights, the backward propagation loss is determined.

Table III
Results of different models on LAG dataset

Models	Alex Net	VGG-11	VGG-16	VGG-19	GoogleNet-V1	ResNet-18	ResNet-50	ResNet-101	ResNet-152
Accuracy	81.4	80	82.2	80.9	82.9	86.7	85.6	86.2	86.9
Precision	81.8	80	82	80.9	82.9	86.7	85.6	86.2	86.9
Recall	81.5	80	82	80.9	83	86.7	85.7	86.2	86.9
Loss	0.4	0.4	0.3	0.4	0.3	0.3	0.3	0.3	0.2

The most relevant deep learning and machine learning algorithms for retinal image processing were discovered in [10], along with their pros and disadvantages. As a result, fundus images allow you to see some of the most critical structures in your eye, such as the blood vessels, optic disc as well as the optic disc cup. Different methods for classification and detection of glaucoma using retinal pictures have been effectively applied in this paper, including machine learning via feature extraction, transfer learning and deep learning. Feature extraction is used in the above-mentioned process of glaucoma detection and involves pre-processing of the input image. The image is then segmented to focus the key characteristics (such as retinal vessels and the optic disc),
which are retrieved and selected for a more accurate categorization of retinal images into glaucoma and non-glaucoma. In [11], Naive Bayes and SVM learning algorithms employed for categorization of 272 retinal images , 100 of them being without the glaucoma and 72 with mild glaucoma. For mild glaucoma detection, the average accuracy was 84.72 percent Glaucoma was detected on retinal imaging utilising cup-to disc ratio CDR (Cup to Disc Ratio) measures, it had a 98.6 percent average accuracy.
Pre-processing was applied in the following method of Transfer learning and Deep learning for standardisation and a more accurate assessment of the fundus images. For better results, region of the images around the optic discs were used. They
used four datasets totaling 788 glaucoma photos and 918 non-glaucoma images. It offered a two-phase approach for early identification of various eye disorders (glaucoma and diabetic retinopathy); the initial phase involved training and testing and the following phase featured a real time GUI (Graphical User Interface) detection. The method's second phase included the creation of a website that allows people to post fundus images. The photos are pre-processed and categorised using CNN, and the results are presented in the form of a confidence percentage, indicating whether the disease is present or not. The results demonstrate, with an accuracy of 80 percent, that previous work was correct.

III. Related Work

There has been a great amount of research done on the "Glaucoma Detection". The work ranges from using machine
learning classification techniques like SVM and Random forest classifier to complex deep learning image classification techniques which include the use of popular CNN models like VGG-16, Alexnet , Resnet-50,Resnet-152 etc via the Transfer
Learning method . Transfer learning takes the advantage of the vital features already learnt by the models trained on large datasets and applies what it has learnt on another problem. When you don't have a large enough dataset for your problem the 'Transfer Learning Method' can be very effective as it was designed specifically for this purpose. One of the research was on the prediction of whether a patient would catch Glaucoma in the Near future based on the medical history of that patient, This is an interesting and important work as it could alert a patient and the doctor about the possibility of the patient catching that disease but the major issue with this is that it requires patients sensitive data such as blood pressure, visual acuity, blood sugar, hypertension, age, family history, etc and this type of data is generally private with the hospitals and very hard to get. The majority of the research focuses on detecting the presence of the disease using CNNs Image classification ,overtime CNNs have become more powerful and keep on improving with the accuracy and with the research accelerating in the field of deep learning we believe that the accuracy can be further improved.

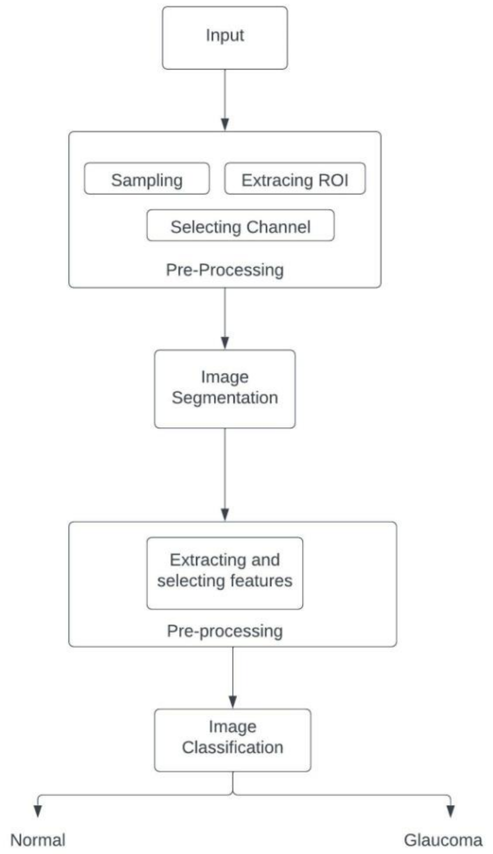

Fig. 14: Block Diagram for Glaucoma detection process

IV. APPLICATIONS

A. It can help detect whether the patient has caught the disease
B. Can aid the doctors as their assistant to confirm their speculations or analysis
C. Since it can predict the output almost instantly it can be applied on several photographs and we can get the result in no time
D. Users can directly check the presence of glaucoma without the need of consulting a doctor

V. CONCLUSION

Various different image classification techniques have been used to solve the problem of glaucoma detection . Glaucoma prediction using a patient's health history is an interesting approach but it is difficult to find the data for that. The more common CNN methods also achieve great results ,the VGG-16 and ResNet-152 seem to give the better results compared to others, the use of transfer learning helps to maintain a great accuracy despite using a smaller dataset for training. The most interesting approach was a 2 step method in which the first step consisted of identifying the optical disc region of the fundus image using RCNN which was followed by the second step in which a dense convolutional regression network was trained for calculating the CDR(cup to disc ratio) this reduced the mean absolute error as well as the mean squared error of a standard CNN model.

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