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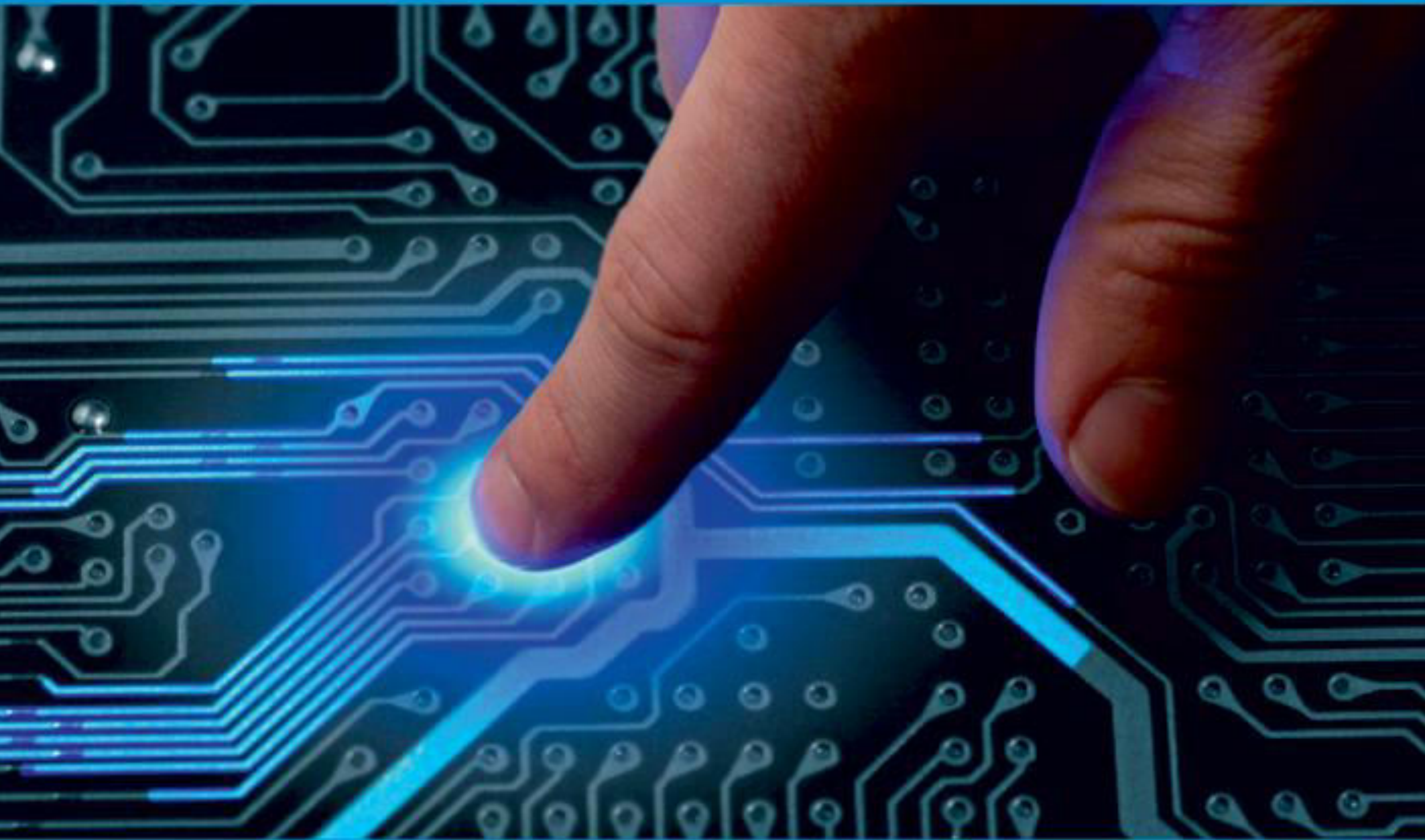

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Glaucoma Detection using Machine Learning Algorithms

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ABSTRACT: GLAUCOMA is an incurable, irreversible eye infection in which the optic nerve is repeatedly damaged. It causes slow, progressive retinal degeneration. Though it cannot be completely cured, the progression of the disease can be slowed by detecting it early on. Glaucoma affects the Optic Head Nerve, whose density is determined by the Optic Cup and Optic Disc measurements.We intend to design a model in which glaucoma can be recognized/detected in the early stages of the disease, preventing additional vision loss. Various techniques, such as CNN, logistic regression, K-nearest neighbours classifier, and Support Vector Machines, can be used.All of these methods can be used to determine the OC and OD dimensions. We intend to leverage a variety of datasets, including ARIA and RIGA and FUNDUS images, which will later be converted into segmented images. Our goal is to compare various machine learning algorithms in terms of various metrics and prove that our model gives the most optimal results

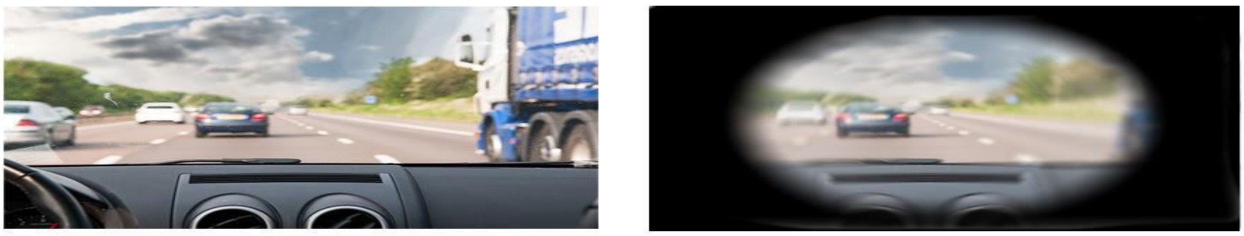
KEYWORDS: Glaucoma, Intraocular Pressure(IoP), ResNet, LAG, ARIA, VGG.

I. INTRODUCTION

A. What is Glaucoma

Glaucoma is a complicated ocular condition in which the optic nerve is injured and vision loss is progressive and irreversible.

Glaucoma causes vision loss that starts in the peripheral areas and can progress to permanent vision loss in some ircumstances. Glaucoma is the second leading cause of blindness in the world, according to the World Health Organization (WHO). The majority of the time theBecause of the increased pressure in the eye, the optic nerve is injured. Intraocular pressure is the term for this. The world's beginnings of Glaucoma may be traced back to the Byzantine and Greek ages, as early as 762 B.C., when it was first mentioned in Homer's poems.Hippocrates coined the term 'glaucosis' to describe the diseases associated with sparkling silver glare' about 400 B.C.Richard Banister, a British ophthalmologist, published the first clear description of glaucoma in 1662. Furthermore, he established a link between increasing eyeball strain and glaucoma.



Healthy eyes   Periphial vision loss due to glaucoma

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

.

B. Causes of Glaucoma

A. High Pressure in the eye- the intraocular pressure: Through the cornea and iris, aqueous humour liquid leaves the eye. Intraocular pressure (IOP) in our eyes might rise if the channels of the cornea and iris are closed or partially occluded. The optic nerve of the eye may be injured if intraocular pressure (IOP) rises..

B. Different reasons to increase Pressure in the eye:

i. Eye drops that dilate the pupils

ii. Drainage in the eye is obstructed or inhibited

iii. The optic nerve has poor or decreased blood flow.

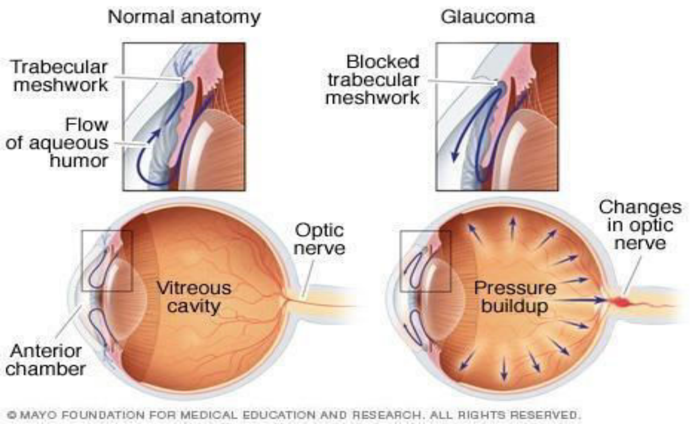


Fig. 2: Intraocular Pressure (IOP)

C. Family history with glaucoma:

D. Eye fluid unable to flow properly.

E. Inflammation within the eye:

F.Extra pigment being dispersed within the eye:

G)Medical conditions like diabetes and high blood pressure:

C. Categories Of Glaucoma

There are mainly two forms of glaucoma. These two forms of glaucoma are open-angle and angle-closure. The increase in intraocular pressure (IOP), or the pressure inside the eye, causes these

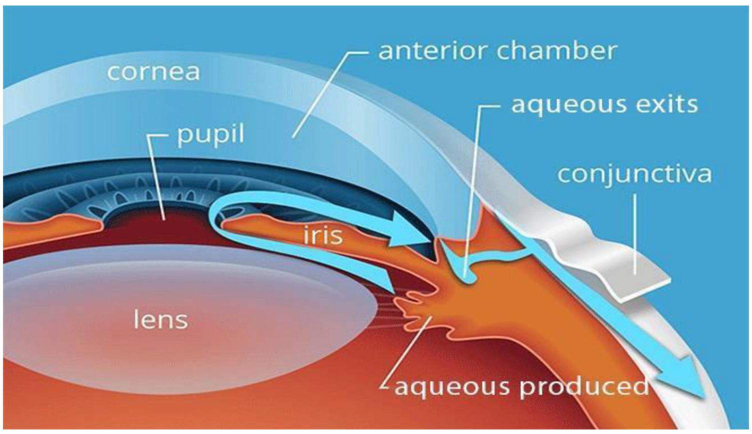


Fig. 3: Human Eye's Anatomy

1) Open-angle Glaucoma: The most prevalent kind of glaucoma is open-angle glaucoma, which affects 90% of patients. Glaucoma can alternatively be referred to as Primary or Chronic Glaucoma. The angle where the cornea meets the iris is referred to as "open-angle," and it is as wide and open as possible.

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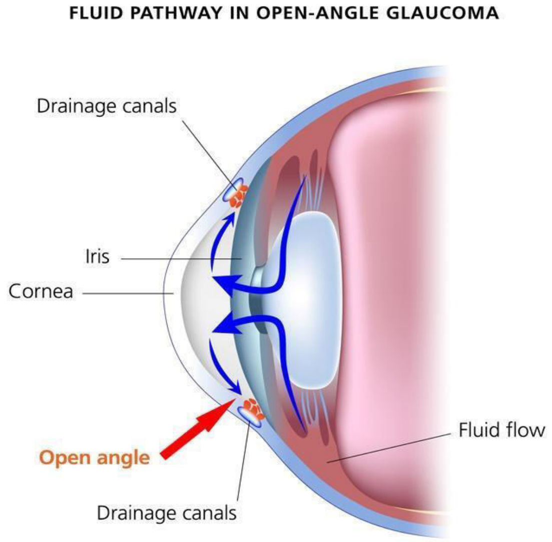

Fig. 4 ; Open Angle Glaucoma

2) Angle-Closure Glaucoma: Glaucoma of this sort is a more uncommon occurrence of glaucoma. Acute or Narrow Angle Glaucoma is another name for it. Angle-closure glaucoma, on the other hand, occurs when the angle between the iris and the cornea closes or is narrow.

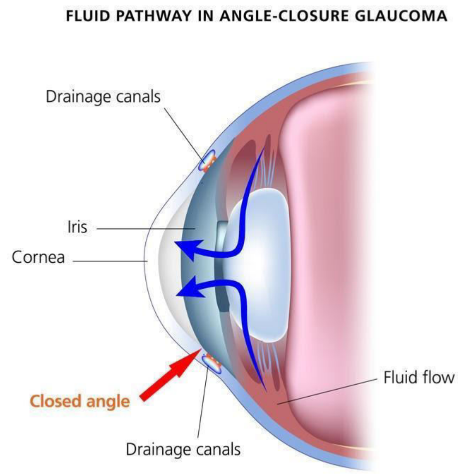

Fig. 5: Angle Closure Glaucoma

D. Fundus Images

The section of a hollow organ that is furthest from the aperture is called a fundus. The fundus of the eye, which includes the retina, macula, fovea, posterior pole, and optic disc, is the posterior membrane of the eyeball. Fundoscopy is a procedure in which ophthalmologists manually examine a patient's fundus with an ophthalmoscope. The technology of optical coherence tomography is used to obtain fundus images of the eye, which can then be utilised to identify and forecast glaucoma disease. The optic disc can be seen in Fundus imaging as a region of brilliant concentric circles of varying brightness.The optic cup is formed by the inner bright circle, the optic disc is formed by the outer bright circle, and the space between the two is formed by the neuroretinal rim. CDR (Cup to Disc Ratio) is shown to be the most essential structural and functional trait for glaucoma detection. (Area of Optic Cup / Area of Optic Disc) is a formula for calculating CDR

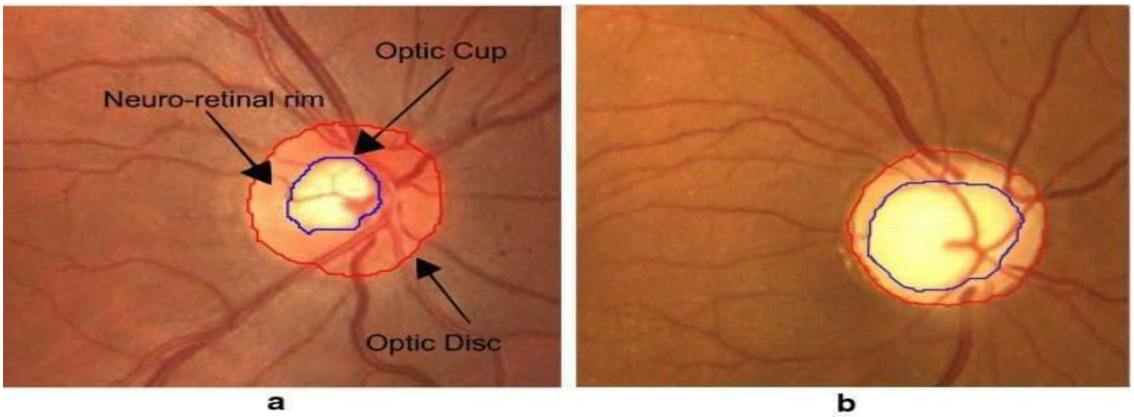

Fig. 6: normal eye image(a) and glaucomatous eye image(b)

II. LITERATURE SURVEY

2.1 **Magnitude and determinants of glaucoma in type II diabetics: A hospital based cross-sectional study in Maharashtra, India** *— Jan 2015*

Authors: Sheetal Dharmadhikari, Kavita Lohiya, Vidya Chelkar, V. K. S. Kalyani, Kuldeep Dole, Madan Deshpande, Rajiv Khandekar, and Sucheta Kulkarni

In this paper authors Sheetal Dharmadhikari, Kavita lohia, Vidya Chelkar, V.K.S Klayani Kuldeep Dhole, Madan Deshpande and a few others suggest that patient health records be used to predict that a patient may develop glaucoma.

The health record contains data such as blood pressure, visual acuity, blood sugar, high blood pressure, age, family history, etc. and other factors that can be considered as personal data of patients. Editing was done using BOSVM, LSVM, MGSVM where the results given by the BOSVM model were more accurate than the other two. The disadvantage of these models is that Iit is difficult to obtain such databases. Although it is a very effective method as it provides accurate results, it is very difficult to obtain the required data sets because such data is sensitive and confidential.

2.2 **A Glaucoma Detection using Convolutional Neural Network.** *--April 2019*

Authors: A. Saxena, A. Vyas, L. Parashar and U. Singh

Arkaja Saxena A.Vyas, L.Parashar and U.Singh proposed a six-layer model in which the first four were converted –layers and the last two layers were fully connected.

CNN(Convolutional Neural Network) 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

The Model was tested on the ORIGA and SCES datasets and the results of the models were compared to the state of the art models the proposed model had the accuracy of 82.2 on the ORIGA dataset and 88.2 on the SCES dataset while the state of the art models had the accuracy of 80.9 on the ORIGA dataset and 85.9 on the SCES dataset

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2.3 "Faster R-CNN and DenseNet Regression for Glaucoma Detection in Retinal Fundus Images

--August 2020

Author: M. Aljazaeri, Y. Bazi, H. AlMubarak and N. Alajlan

Manar Aljazaeri , Y.Bazi ,H. AlMubarak and N. Alajlan in the August of 2020 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.

They used their proposed model on 2 different datasets(MESSIDOR and Magrabi)
and compared the results to Unet models performance on the same datasets and the proposed model worked better,Both MAE and MSE indicated the same.

The proposed method (RCNN detection followed by DenseNet regression) gives better performance performance compared to standard segmentation followed by CDR calculation from the predicted masks upto 71% of reduction in MAE

A. ResNet (Residual Network)

VGG-19's 34-layer simple network architecture, wherein the shortcut connections are provided between certain layers, inspired ResNet's implementation. These shortcut connections is what really turn the design into a residual network, as shown in the diagram below. Amer Sallam et al [1] introduced a transfer learning-based feature extraction model. The LAG dataset (large scale attention based glaucoma) was used.

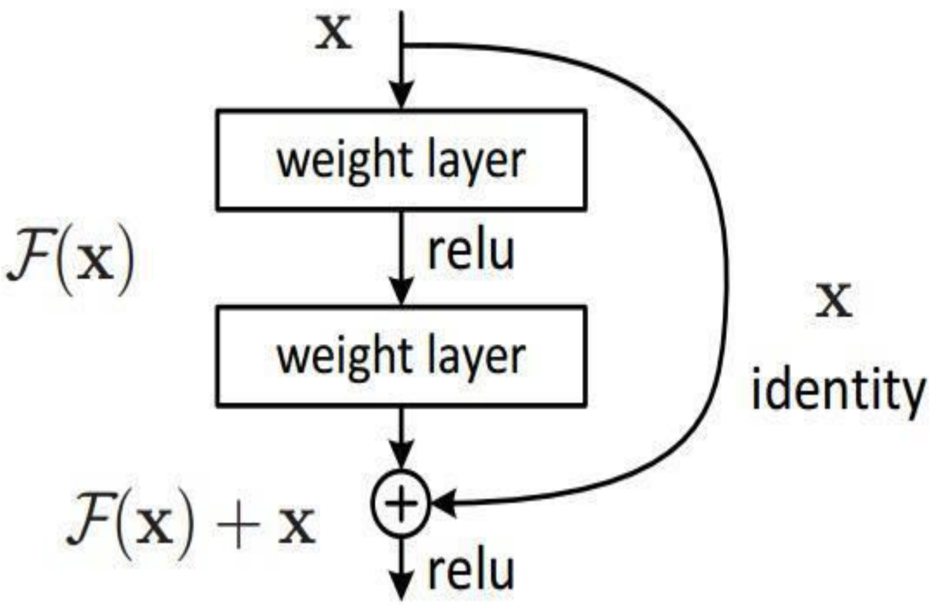

Fig 10. Residual Network

Changes in last (classification) layer were made to adjust the pre-trained models for the glaucoma dataset. Alexnet, VGG-11, VGG-16, VGG-19, Googlenet (inception V1), and a few ResNets such as the ResNet-50, ResNet-101, ResNet-152, and ResNet – 18 On the given dataset, ResNet-152 had the best precision, accuracy, and recall performance metrics of all the transfer learning models listed. The necessity for large datasets for deep learning models

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has been overcome using transfer learning techniques.

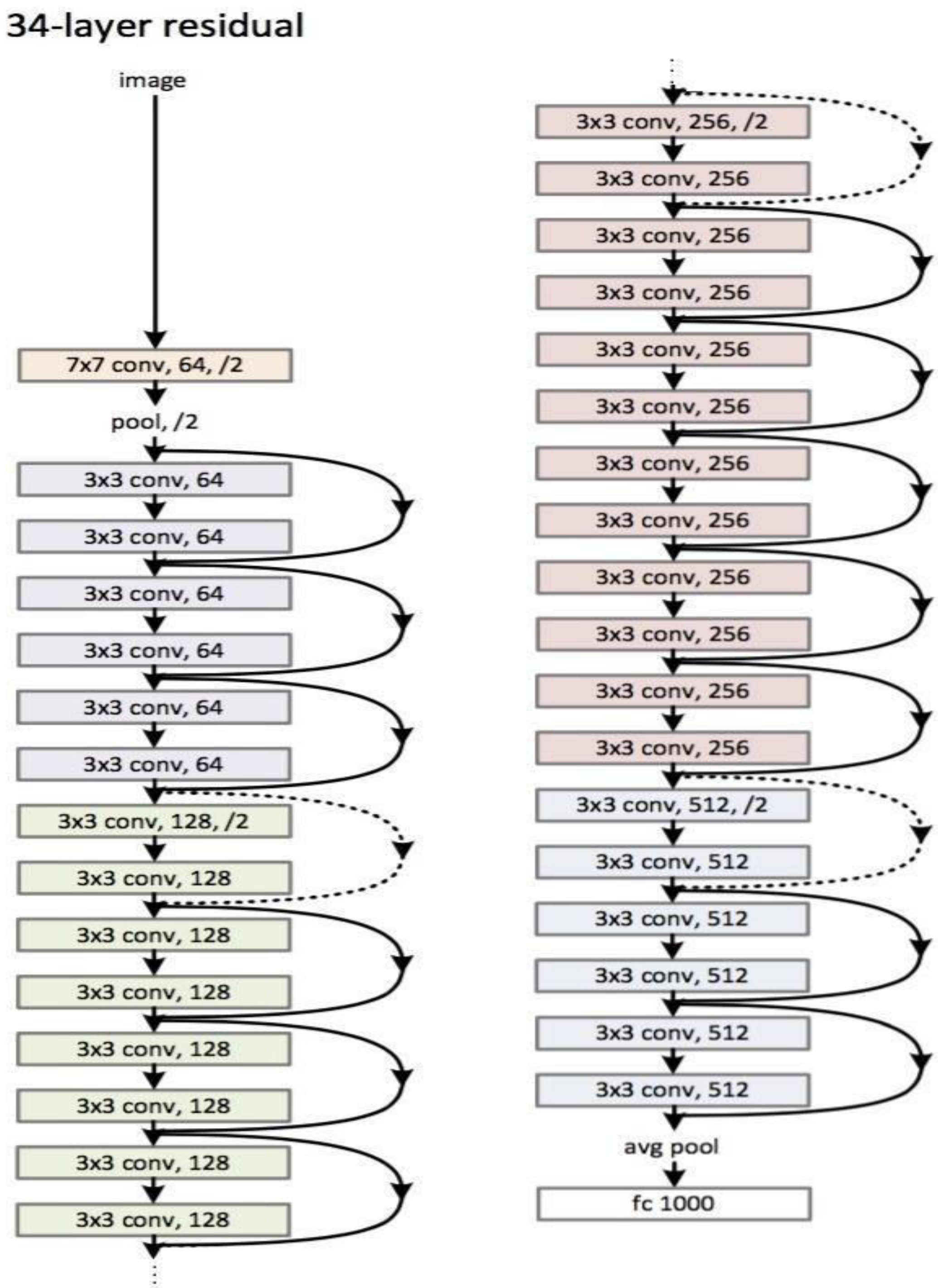

Fig 11. Structure of Residual Network

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B. VGG-16(Visual Geometry Group)

K. Simonyan , A. Zisserman of Oxford University proposed VGG-16. The model is called a Convolutional Neural Network (CNN). On the ImageNet dataset, which has 14,000,000 images and over 1000 classes, it achieves 92.5 percent accuracy. VGG-16's architecture is depicted in the diagram above. Its advantage over the AlexNet model is that it employs numerous 3*3 kernel-sized filters sequentially rather than the big kernel-sized (5 in the second layer and 11 in the first layer) filters employed by AlexNet.It needs a lot of processing resources, time, and datasets to train because of its depth and tightly connected layers. As a result, tools like tensorflow and keras provide pre-trained VGG-16 models that can then be fine-tuned locally on specific datasets. Global thresholding was employed by Anuradha Panday et al [9] to extract the basic specifications from fundus images such as optic disc radius, optic cup radius, and intern CDR (cup to disc ratio). Images were taken from a variety of public databases. The following categorization models used these extracted features as input. VGG-16, SVM, LDA, KNN, Decision Tree The accuracy of the KNN and VGG-16 models was 98 percent.

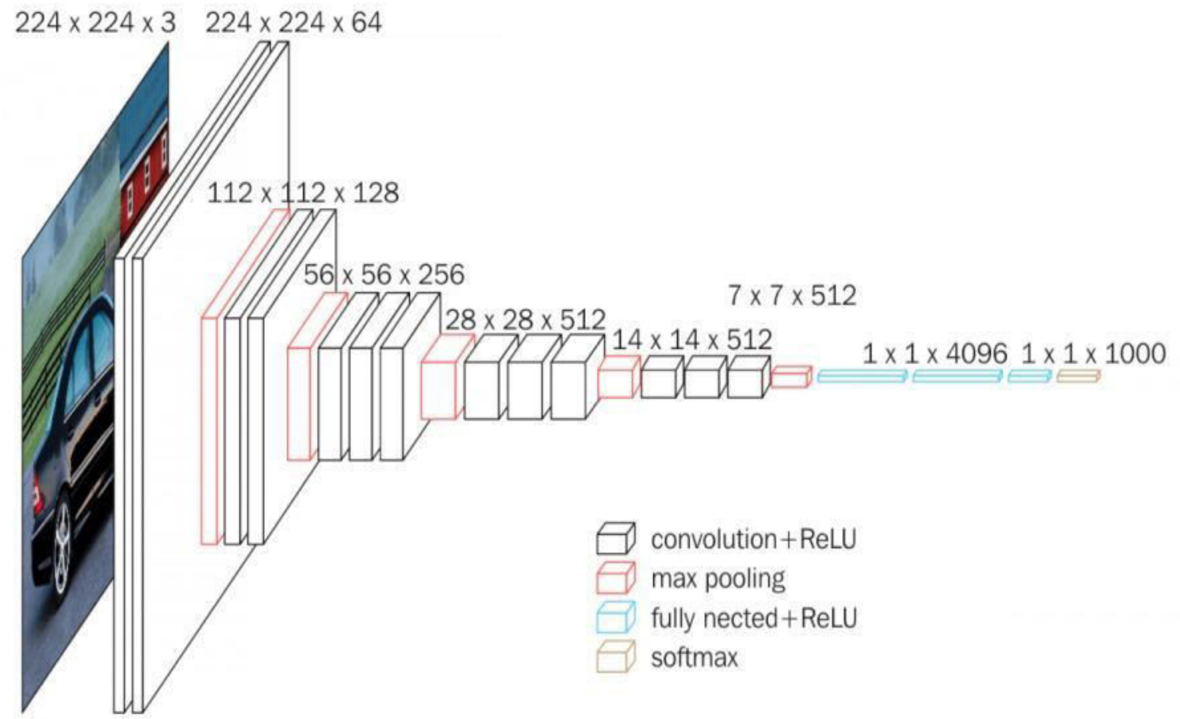

Fig 12. Structure of VGG

C. Efficient Net

It is just a model for scaling convolutional neural network models that has been rethought. The depth, width, and clarity of the convolutional neural network may all be tweaked separately. The number of network layers determines the depth of the network. The number of neurons in the layer, or more precisely, the number of filters in the convolution layer, is related to the width. The length and width of an image are referred to as resolution. The graphic below illustrates the scaling in all three dimensions.

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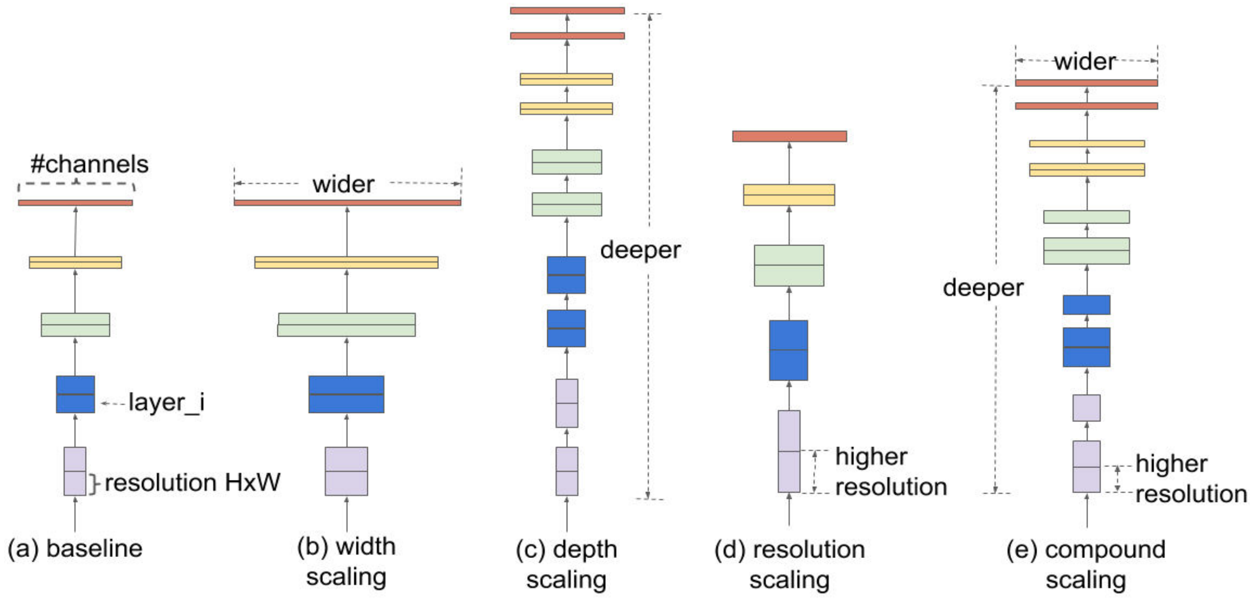

Fig 13. Comparing different scaling techniques.

Ana-maria Stefan et al [10] gave a quick rundown of the various glaucoma detection methods. The primary methodology for classifying fundus images include feature extraction-based machine learning methods, deep learning and transfer learning techniques. The first class of strategies is locating a region of interest, extracting features, and then classifying the data based on the recovered features. For classification, the second class of strategies use deep learning and transfer learning models directly. In comparison to 80 percent of earlier works, the methods in second class produced superior results. De La Fuente-Arriaga et al. [7] detected glaucoma by employing vascular displacement values computed from the growth of holes in the OD and OC. Glaucoma detection with fundus pictures was presented by Acharya et al. [8].An adaptive histogram was utilised to eliminate noise and improve image contrast in this case. To build a binary image, each pixel is compared to its neighbouring pixel, which is then utilised that generate values to signal the presence of glaucoma via sequential forward search. Initially, data augmentation is used on the training data to increase the number of samples in the data. The transfer learning model is then trained using backward and forward propagation approaches. Forward propagation characteristics are extracted using convolutional layers with many filters. The backward propagation loss is calculated to update the weights.

D. UNet

U-Net is a semantic segmentation architecture. It has two paths: one that contracts and one that expands. The convolutional network's contracting path follows the standard architecture. It comprises of two 3x3 convolutions (unpadded convolutions) that are applied repeatedly, each followed by a rectified linear unit (ReLU) and a 2x2 max pooling operation with stride 2 for downsampling. We quadruple the number of feature channels with each downsampling step. An upsampling of the feature map is followed by a 2x2 convolution ("up-convolution") that halves the number of feature channels, a concatenation with the proportionally cropped feature map from the contracting path, and two 3x3 convolutions, each followed by a ReLU in the expansive path. Due to the loss of boundary pixels in every convolution, cropping is required. A 1x1 convolution is employed at the final layer to transfer each 64-component feature vector to the desired number of classes. The network comprises a total of 23 convolutional layers.

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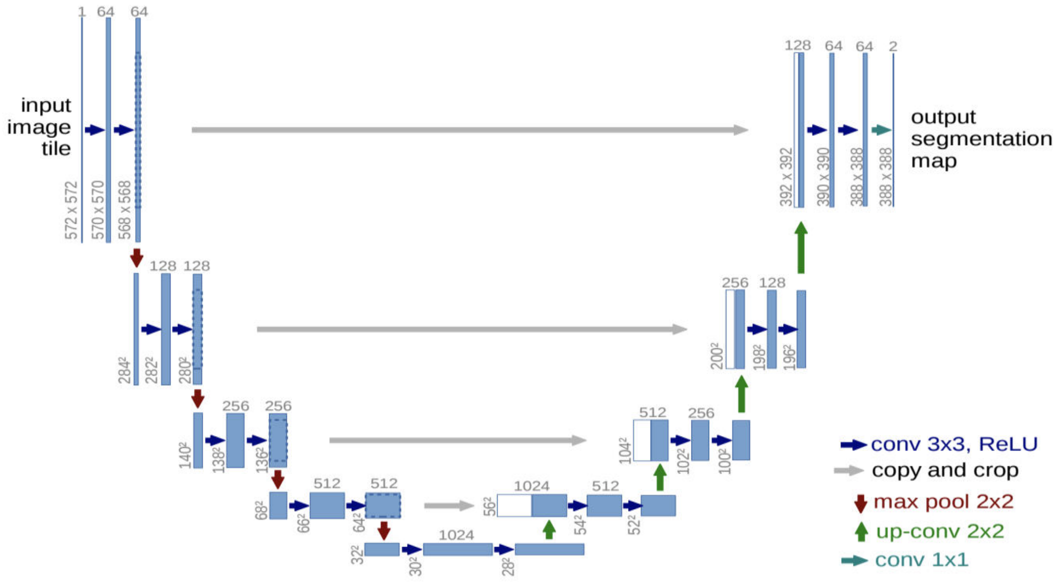

Table III
Results of different models on LAG dataset

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 methods for retinal image processing, as well as their benefits and drawbacks, were discovered in [10]. As a result, fundus images let you to observe some of your eye's most important components, such as blood vessels, the optic disc, and the optic disc cup. This article successfully employed a variety of methods for classification and diagnosis of glaucoma using retinal images, including machine learning via feature extraction, transfer learning, and deep learning. The above-mentioned glaucoma detection process employs feature extraction, which entails pre-processing of the input image.The image is then split to focus on essential features (such as retinal vessels and the optic disc), which are then retrieved and selected for a more precise classification of retinal images as glaucoma and non-glaucoma. [11] used Naive Bayes and SVM learning algorithms to categorise 272 retinal pictures, 100 of which were free of glaucoma and 72 of which had mild glaucoma. The average accuracy for mild glaucoma identification was 84.72 percent. Glaucoma was recognised with 98.6 percent accuracy using cup-to-disc ratio CDR (Cup to Disc Ratio) parameters on retinal imaging.

For standardization and a more accurate assessment of the fundus images, pre-processing was used in the following methods of Transfer learning and Deep learning. The region of the photos around the optic discs was employed for better outcomes. They used a total of 788 glaucoma photographs and 918 non-glaucoma shots from four databases. It featured a two-phase technique for early detection of various eye problems (glaucoma and diabetic retinopathy), with the first phase involving training and testing and the second phase involving real-time GUI (Graphical User Interface) detection. The second part of the process entailed the construction of a website where users may upload fundus photos. The images are pre-processed and classified using CNN, with the results provided as a confidence percentage indicating whether or not the disease is present. The findings show that previous work was correct, with an accuracy rate of 80%.

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II. Proposed Model

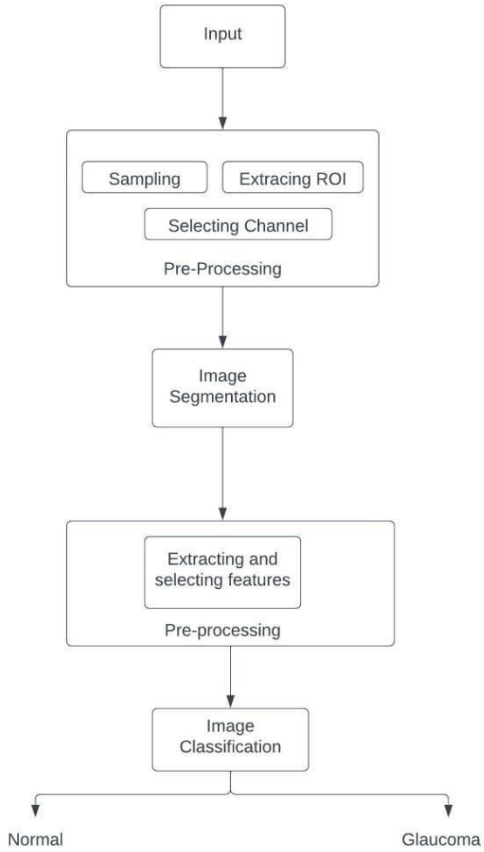

Fig. 14: Block Diagram for Glaucoma detection process

The above figure shows the flow of the model, first the fundus images undergo the necessary pre-processing,then the algorithm is trained to recognise the optic cup and optic disc. The metric used to determine how well the trained algorithm detects the OC(optic cup) and OD(optic disc)

is iou(intersection over union) which is defined by the ratio of the intersection of areas of actual OD or OC and The predicted OC or OD over the union of areas of actual OD or OC and The predicted OC or OD. This part is known as 'segmentation', for the purpose of segmentation we use a very popular encoding technique called 'UNet encoding' , it is best suitable for all types of segmentation problems and used widely in the field of medical sciences.

Then for classification we use the help of the results achieved from the segmentation problems , CDR is a very crucial and determining factor for glaucoma.Hence when we get OC and OD from segmentation we use the the classification model to classify the images into glaucomatous or non-glaucomatous ,for classification we use the Efficient Net model. It is known to be the state of the art model in the field of image classification.Various metrics like accuracy , sensitivity ,specificity etc are used to evaluate the classification model.

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III. RESULT AND EVALUATION

- We have used 4 different machine learning models namely the Efficient net b4, Efficient Net b0, ResNet-152 , VGG-19.
- We have used the above mentioned models on 3 datasets 1)DrishtiGS 2)ORIGA 3) REFUGE
- We have used 2 types of evaluation metrics a)Segmentation metrics and b)Classification Metrics.
- Segmentation metrics include the iou score OD, f1score OD , iou score OC, f1score OC.
- The Classification metrics include specificity , sensitivity , balanced accuracy , accuracy , precision
- The following tables describe the results of each model on each dataset

DRISHTIGS- Segmentation

Models	F1 Score (OC)	IOU Score(OC)	F1 Score (OD)	IOU Score(OD)
B0	0.9460	0.9034	0.9826	0.9663
B4	0.9486	0.9089	0.9814	0.9697
VGG	0.9822	0.8820	0.9710	0.9467
ResNet150	0.9468	0.9052	0.9816	0.9645

Table 4. DrishtiGs Segmentation Results

DRISHTIGS- Classification

Models	B0	B4	VGG	ResNet152
Accuracy	80.39	84.31	71.54	80.3921
Sensitivity	0.9473	0.9210	0.7894	0.8421
Specificity	0.9846	0.6153	0.5384	0.6923
Balanced Accuracy	0.6659	0.7682	0.6639	0.7672
Precision	0.8181	0.8755	0.8333	0.8888

Table 5. DrishtiGs Classification Results

ORIGA segmentation:

Models	F1 Score (OC)	IOU Score(OC)	F1 Score (OD)	IOU Score(OD)
B0	0.9997	0.8927	0.9767	0.9553
B4	0.9396	0.8926	0.9824	0.9660
VGG19	0.9295	0.8772	0.9782	0.9583
ResNet152	0.9341	0.8843	0.9836	0.9683

Table 6. ORIGA Segmentation Results

ORIGA classification:

Models	B0	B4	VGG	ResNet152
Accuracy	74.61	75.38	73.07	73.07
Sensitivity	0.2098	0.1470	0.2058	0.2058
Specificity	0.9315	0.0.9687	0.9166	0.9166
Balanced Accuracy	0.5716	0.5570	0.5612	0.5612
Precision	0.5384	0.625	0.4666	0.4666

Table 7. ORIGA Classification Results

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REFUGE segmentation:

Models	F1 Score (OC)	IOU Score(OC)	F1 Score (OD)	IOU Score(OD)
B0	0.9997	0.8927	0.9767	0.9553
B4	0.9256	0.8736	0.9761	0.9545
VGG19	0.8882	0.8123	0.9296	0.9149
ResNet152	0.9092	0.8483	0.9725	0.9485

Table 8. REFUGE Segmentation Results

REFUGE classification:

Models	B0	B4	VGG19	ResNet152
Accuracy	74.61	71.53	70.0	73.07
Sensitivity	0.2098	0.075	0.05	0.2058
Specificity	0.9315	1.0	0.9888	0.9166
Balanced Accuracy	0.5716	0.5375	0.5194	0.5612
Precision	0.5384	1.0	0.666	0.4666

Table 9.REFUGE Classification Results

❖ **Variation of iou and error with respect to epochs**:

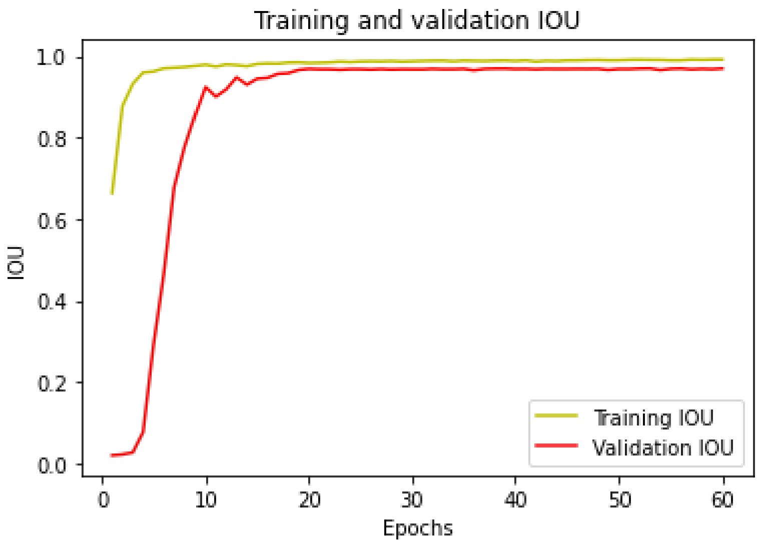

Fig 20. Variation of iou and error with respect to epochs

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- **epochs vs iou (As the epochs increase iou increases and approaches 1)**

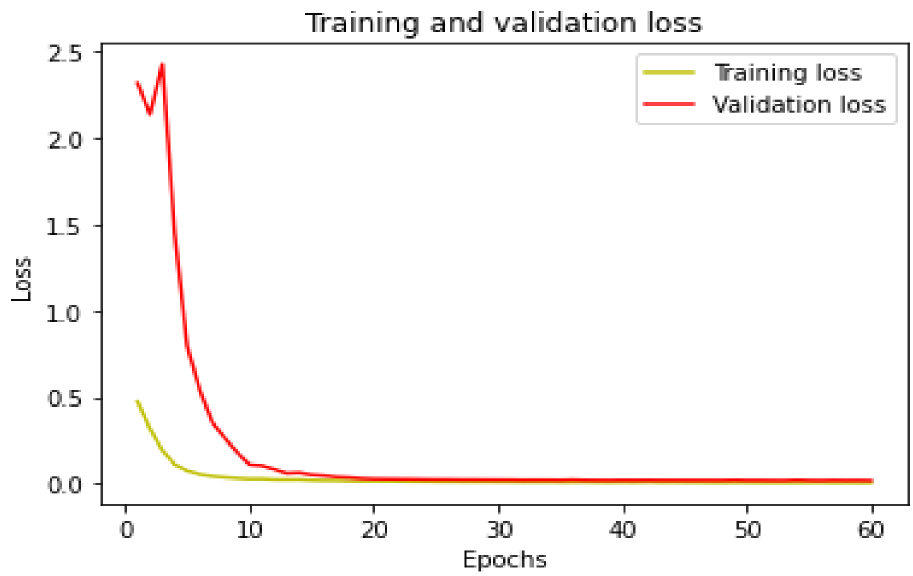

Fig 21. epochs vs iou

- **epochs vs loss (As the epochs increase loss decreases and approaches 0)**

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

After training and fine tuning 4(Efficient NetB0,Efficient NetB4,ResNet-152 and VGG-19) models over 3 datasets(DrishtiGS, ORIGA and REFUGE) and tracking all the results we came up with the following conclusions

- Deep learning models give more accurate results for glaucoma detection.
- The more generalized CNN methods also achieve great results ,the VGG-19 and ResNet-152 seem to give the better results compared to and other VGG and ResNet models.
- EfficientNet model outperformed ResNet and other models.
- Making use of transfer learning and the knowledge of complex deep learning algorithms to get more accurate results for glaucoma detection.
- Because of transfer learning there is no need of huge data sets and processing power for training deep neural nets models

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- Automated system for glaucoma detection will facilitate more and more patients to get tested and hence reduce the bad effects of glaucoma.

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