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Real Time Segmentation and Classification of Glaucoma Optic Nerve Head using Improved Y-UNET

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ABSTRACT: Improved Y-UNet model that can be used to generate discriminative masks for the diagnosis of glaucoma. In this research have developed a method that combines the mapping properties of disc and optic cup to identify regions in an image. Improved Y-UNet (Yolo-UNet) is a network extension that extends and generalizes Y-UNet. It provides a parallel branch for discriminate map generation and supports various network efficiency tweaks. Improved Y-UNet features an improved diagnostic classification algorithm that learns fewer parameters than its competitors. The proposed model for classification of glaucoma is proposed in this research. It is mainly used for determining the type of glaucoma disease and its classification accuracy. The recognition and positioning of the Optic Nerve Head (ONH) is very important for early detection of glaucoma and other eye disorders. It can be done by examining the blood vessel retinal rim pattern. The process involves the use of Sensitive Mirror Analyzer and Retina Tracker (SMART) technology. The proposed method has been shown to provide better accuracy and sensitivity than the existing method.

KEYWORDS: Improved Y-UNet, Cup-to-Disc ratio, Optic Nerve Head, U-Net, SMART technology

I. INTRODUCTION

Glaucoma [1] is one of the major eye diseases that affect millions of people globally. It is very important that we know about this condition and its symptoms. The brightest portion of a retinal image is the optical disc. It has a diameter of 1.8 mm and measures 2.1 mm thick. Evaluation of CDR (Cup to Disc Ratio) [2] is done by measuring the boundaries of the optical disc and the optic cup.

The ISNT rule [3] is used to evaluate the thickness of the rim in the healthy eye. However, it is not used to detect glaucoma if the size of the optic region widens. The ISNT rule can be easily analyzed in retinal fundus images by estimating the cup to disk ratio. This ratio can be used to identify glaucoma or normal shows in figure 1.

Glaucoma [4] is a serious eye disease that can be easily categorized through the use of artificial intelligence. This technology can help improve the accuracy of diagnosing this condition. This paper improve the localization of the disk area by analyzing the optical disc and cup sizes. This data can be used in the preparation of the proposed improved Y-UNet model.

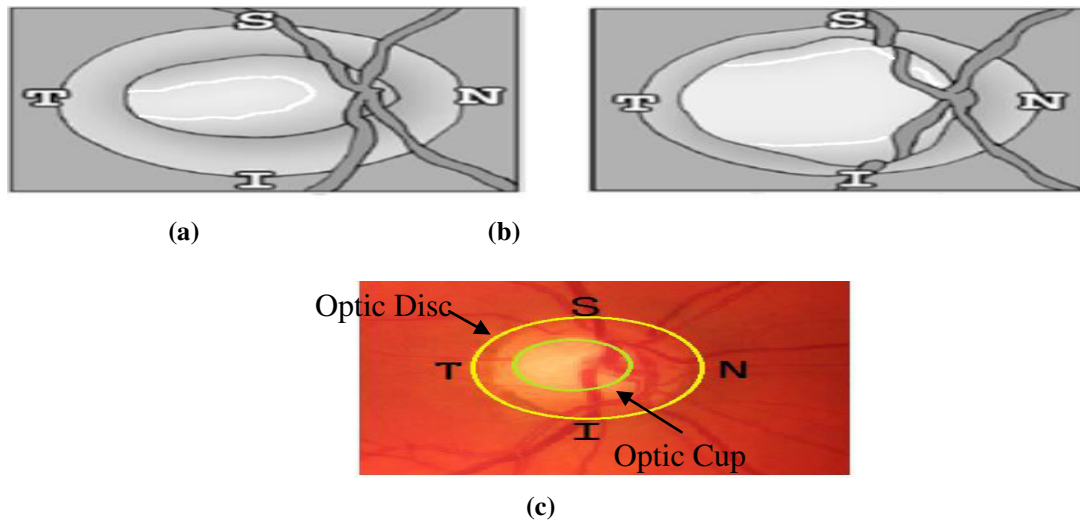


Fig: 1 Both healthy (a) and abnormal (b) retinal fundus images were obtained from the ISNT rule(c). The images exhibited superior and inferior features.

This paper presents the improvement of the localization [5] of the disk area through the use of optic disc and cup data. It allows the preparation of the necessary steps for classification. CNN aims to learn and exploit the features of an image to make it more nuanced. Still, in image segmentation, it need to convert the feature map into a vector and reconstruct it. While converting an image to a vector, usually learn how to map the feature mapping of the image to the vector. This would preserve its structural integrity and prevent it from distorting.

In Image segmentation, the machine has to divide the image into various segments, each of which has a different entity. Convolutional Neural Networks are good at simplifying image segmentation problems, but they are not very effective at tackling complex ones. This is where UNet comes in. In the research, to enhance UNet performance segmentation and classification. So this paper plan to modify improved Y-UNet model. The process involves the use of Sensitive Mirror Analyzer and Retina Tracker (SMART) technology [6].

II. RELATED WORK

This paper have developed a method to sequentially combine two different models to solve a large problem. In the past, classification and segmentation have been considered as part of the disease models for glaucoma.

This paper shows that can be combined using the output of a classification model. In previous research, UNet only used for segmentation. But the proposed Improved Y-UNet model specially used for segmentation and classification also.

Pardhaet. al.[7] used the boundaries of ocular diameter (OD) and cup segmentation to identify glaucoma. The data collected were then used to automatically diagnose and monitor glaucoma. Srinivasan et.al., [8] approached for automatic segmentation of an optical disc using pixel intensity analysis is presented. It is performed through a simulation software and hardware platforms.

Mohammad et.al., [9] suggested a set of stationary wavelet transform features was used to generate three in-region cost functions with respect to cup, rim, and contextual regions. The disc-boundary cost function was trained using a random forest classifier. Sumanet. al., [10] planned optical disc segmentation were performed simultaneously using regression based method. The data augmentation method was also used to train the cascades.

Yuvan et.al,[11] proposed a well-known structure relationship between the optic disc and cup, and extend the model to include the multi-dimensional feature space. Fengshou et.al.,[12] proposed method to segment an optical dimension or an optical center from digital color images using a statistical deformable model. The model was used to test the correctness of the method. Joshua et.al. [13] proposed model performed better than others in terms of the dice-score and



the prediction time. Deep learning methods were proposed to enable us to segment the image into two parts, which are the ocular and the occipital.

Existing research methods used for cup segmentation were based on grayscale image. Some existing methods try to produce a set of probable pixels that are appropriate to cup size. A set of potential pixels has been developed that corresponds to the cup boundary.

This paper have developed a method to smooth the boundaries of an optical disk segment by using ellipses [14]. This method is applicable for both optical cup and optic disk segmentation [15]. This paper combine the input of a segmentation model and a classification model to classify the retinal fundus image.

III. METHODOLOGY

Improved Y-UNet follows a same architecture as U-Net. It has a few modifications. Improved Y-UNet is an architecture that can be used for programming with independent convolution based UNet. The depth wise improved Y-UNet is a type of channel-wise convolution.

3.1 Architecture of SMART Technology

The operation is mainly used for extracting boundaries from blood vessels. It is also used for Resizing, Noise removal, and Transformation. A convolutional layer increases the receptive field of a patch classifier. Figure 2 shows the capture of video using a SMART system camera. It shows the fundus image with a resolution of 320 x 320 pixels. The average size of a disc is 1.77 mm and the average size of its vertical dimension is 1.88 mm. The correction factor (c_f) will be determined by on which power high plus lens,

$$c_f = 1.0 \text{ mm} \rightarrow +60\text{D lens} \quad (1)$$

$$c_f = 1.11 \rightarrow +78\text{D lens} \quad (2)$$

$$c_f = 1.33 \rightarrow +90\text{D lens} \quad (3)$$

This model have 5 channels and 5 nxn longitudinal convolution. Point wise convolution 1x1 is the one that changes the dimension.

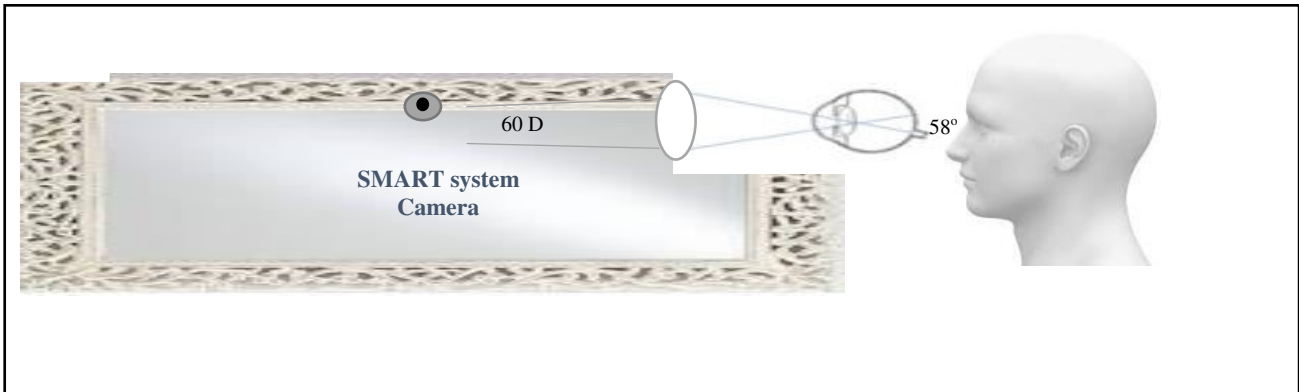
3.2 Preprocessing

The Kalman filter is a fast and flexible algorithm that automatically separates the signals from the noise in a system. It can be used for continuous monitoring and analysis of various systems. It can also detect objects in the environment that can cause visual hallucinations.

It can also prevent visual hallucinations caused by noise. Due to the increasing popularity of video streaming, it has raised the concerns of image quality degradation. This filter is a type of algorithm that uses random signals to minimize an estimated error. Kalman filters are used to estimate states based on linear dynamical systems in state space format. The process model defines the evolution of the state from time $k - 1$ to time k as:

$$x^k = Fx^{k-1} + Bu^{k-1} + w^{k-1} \quad (4)$$

where F is the state transition matrix applied to the previous state vector x^{k-1} , B is the control-input matrix applied to the control vector u^{k-1} , and w^{k-1} is the process noise vector that is assumed to be zero-mean Gaussian with the covariance σ_k^2 . YOLOv5 is used to detect sclera in the video capture image after de-noising.



3.3 Feature Extraction

The images were rescaled to fit the size of the eye. A region around the image center was also used for analysis. Images were padded with small pixel representations on the edges to minimize noise. The features were then extracted in two steps. The first step involved extracting the topography and reflectance images. The second step is the adaptive selection of the wavelet features. Wavelet is a type of algorithm that takes advantage of the frequency selective processing of an image. It can detect the high or low frequency of an image. In this paper consider the various features of the decomposition coefficient found in the original signal shows in figure 3.

Using eq. (5) to (11), find Feature Extraction (FE) particularly focus sclera feature extraction,

$$FE_{sclera} = (R_{sclera} * R_{eyelid}) - R_{sclera} \quad (5)$$

Here, R_{eyelid} indicates eyelid of retina and R_{sclera} indicates sclera of retina. FE_{sclera} , denotes Feature Extraction of Sclera. This research, analyse sclera for optic nerve area detection. So focus frame of sclera,

$$R_{fsclera}(r, s) = \sum_{r',s'} r', s' (P(r's' - I(r + r', s + s'))^2) \quad (6)$$

Where, $I(r, s)$ denotes image, $P(r, s)$ is the Pattern, $R_{fsclera}(r, s)$ is the frame of sclera in the retina of the eye, $r' = 0, w - 1$ and $s' = 0, \dots, h - 1$.

$$FE_{fsclera}(r, s) = \frac{\sum_{r',s'} r', s' (P(r's' - I(r + r', s + s'))^2)}{\sqrt{\sum_{r',s'} (P(r's'))^2 \cdot \sum_{r',s'} I(r + r', s + s')^2}} \quad (7)$$

$$FE_{fsclera}(r, s) = \frac{R_{fsclera}(r,s)}{\sqrt{\sum_{r',s'} (P(r's'))^2 \cdot \sum_{r',s'} I(r + r', s + s')^2}} \quad (8)$$

$FE_{fsclera}(r, s)$ is the result of Feature Extraction of sclera frame in the retina image. In this research, create a yellow colored rectangle box, which is centered in the retina of the eye. Pattern matching is done here on a frame by frame basis.

Here, find the location of the pattern in a retina image where the value is lowest. It is defined as follows:

$$R_{sclera}(p, q) = \sum_{p',q'} p', q' (P(p'q' - I(p + p', q + q'))^2) \quad (9)$$

where, $I(p, q)$ denotes image, $P(p, q)$ is the Pattern, $R_{sclera}(p, q)$ is the result of sclera, $p' = 0, \dots, w - 1$ and $q' = 0, \dots, h - 1$. At every single location, a metric is calculated. So it denotes how related the patch is to that specific area of the image.

For every location of $P(p,q)$ over $I(p,q)$, it stores the metric in the result matrix $R(p, q)$. Each position (p, q) in R contains the match metric.

This research, use in normalized form to divide the value of sum with the following expression,

$$FE_{sclera}(p, q) = \frac{\sum_{p',q'} p',q'(P(p'q'-I(p+p',q+q'))^2)}{\sqrt{\sum_{p',q'} (P(p'q'))^2 \cdot \sum_{p',q'} I(p+p',q+q')^2}} \tag{10}$$

$$FE_{sclera}(p, q) = \frac{R_{sclera}(p,q)}{\sqrt{\sum_{p',q'} (P(p'q'))^2 \cdot \sum_{p',q'} I(p+p',q+q')^2}} \tag{11}$$

$FE_{sclera}(p, q)$ is the result of Feature Extraction of sclera in the retina image. This process creates the identify feature more useful. In normalized can know more about the percentage of matching.

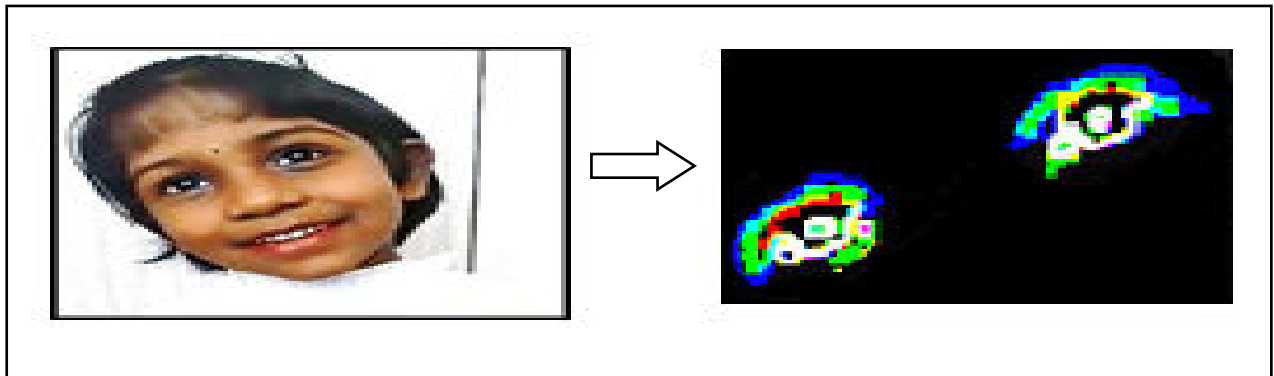


Fig. 3 Feature extraction of Sclera area using the proposed Improved Y-UNet model

3.4 Object Detection

YOLO produces the corners of the rectangle, which are the coordinates of the UNET output boxes. In this paper will show how to output the corners of a rectangular image using yolov5v. This method will enable us to crop the image properly. This paper have to find a threshold first to get the number of pixels that are not zero.

The YOLOv5, YOLOv5n release includes a host of new changes across 465 PRs, with a focus on the new P5 and P6 nano models. The new micro models are very small and can run on both mobile and SMART Mirror. The YOLOv5 micro models are very small and have a slightly improved performance compared to their predecessors. This training is run on a dataset containing over 50 YOLOv5n epochs.

The Backbone uses CSP Darknet [22] to perform feature extraction from images with cross-stage partial networks. Backbone and YOLOv5 Neck rely on CSPDarknet to extract feature data from images. Euclidean distance is more prevalent in larger bounding boxes. Since it affects the size of the boxes, it tends to cause errors. The distance formula is defined as:

$$D(box, centroid) = 1 - IOU(box, centroid) \tag{12}$$

where D represents distance, box represents the sample, and centroid represents the center of the object, and $IOU(box, centroid)$ represents the intersection of the object's center box and the object box. The final distance can be calculated as,

$$D(box, centroid) = \left[\frac{R_b \cup P_b - R_b \cap P_b}{R_b \cup P_b} \right] \tag{13}$$

Here, R_b represents the real box, and P_b represents the prediction box. As stated above, YOLOv5-nano algorithm has achieved end-to-end training and high-speed target detection shows in figure 4.

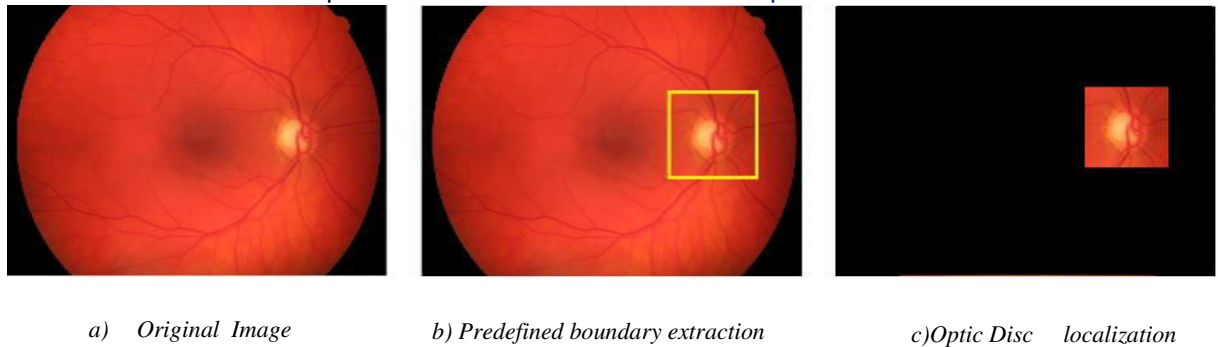


Fig. 4 Detection of Optic Disc Location using Yolov5; yellow square box indicates region of interest of Disc

3.5 Elimination of Blood Vessel

The Image of Blood vessels is acquired by transforming each pixel into a blood vessel. This process eliminates the blood vessels from the image. A morphological procedure [16] that removes blood vessels from a retinal fundus image. It involves applying a black hat to a red channel shows in figure 5.

The image is then followed by the OC boundary smoothing and the circular Hough transformation. The transformation is performed to identify the circle with an unidentified radius. For each red, green, and blue channel image, replace the average of the blood vessel pixel intensity values in its adjacent image.

The morphological approach is used for the enhancement and detection blood vessels. This enhancement can improve the perceptibility of an image while performing manual segmentation and detection techniques for blood vessels. It is also used to extract the components of an image.

In morphological reconstruction process, the image is reconstructed by dilating the image and restoring the information that was not removed. The image is used as a mask or marker for reconstruction. It is mainly used to suppress the bright regions in the image. In image 'f' input, S is the structure element of disk type and C its complement. The top-hat and the bottom-hat transformations are performed respectively.

$$f1 = (f + (f - foS)) - ((f.S) - f) \tag{14}$$

$$f2 = (f + (\max((f - foS), (f - (foC)) - (\max(((f.S) - f), (f.C) - f))) \tag{15}$$

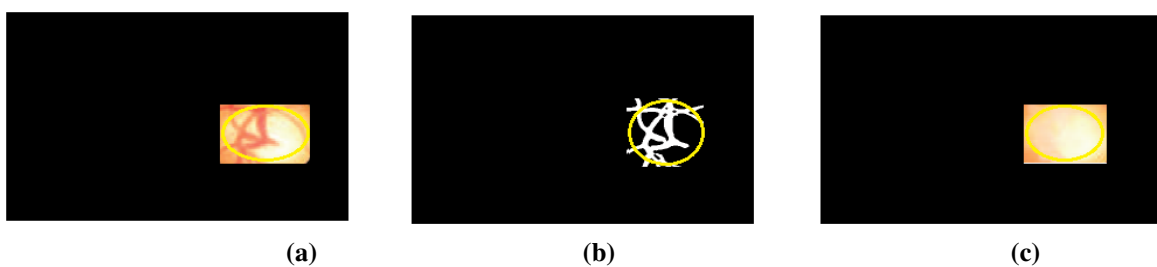


Fig 5. Entirely eliminating blood vessels from the retinal fundus image using morphological operation

3.6 Optic Disc and Cup Segmentation

This procedure is mainly used for disc smoothing. It uses ellipse fitting [17-19]. It is also used for smooth cup boundaries. Figure 2 shows the video capture using a SMART system event camera. It shows the fundus image with a resolution of 320x320 pixels. This procedure is mainly used for extracting blood vessels boundaries. It is also used for



resizing, noise removal, and transformation. A patch classifier is composed of a disc and its receptive field is proportional to the size of the disc [20].

$$CIoU = IoU - \left(\frac{\text{center distance squared}}{\text{convex diagonal squared}} \right) - \left(\frac{v^2}{(1-IoU)+v} \right) \quad (16)$$

$$L_{YUNet} = 1 - CIoU \quad (17)$$

$$L_{UNet} = 1 - IoU = 1 - \frac{\sum I_t o I_p}{\sum (I_t + I_p) - \sum (I_t o I_p)} \quad (18)$$

$$YUNet = L_{CIoU} + L_{UNet} \quad (19)$$

IV. THE PROPOSED IMPROVED Y-UNET FRAMEWORK

Improved Y-UNet is a framework that provides segmentation and classification framework. The goal of this design is to provide a multi-scale representation of the abstract representation of U-Net, so that it can be used to segment and detect classify objects. The following two models yolov5 and UNet are then merged into one single model, Y-UNet and expand the proposed Improved Y-UNet model to perform classify the objects. This model can be optimized to minimize the addition of loss functions. Figure 6 shows functional model of proposed improved Y-UNet. Red square indicates function of object detection and feature extraction. Blue square box indicates function of segmentation. Green square indicates function of classification. Performance of improved Y-UNet model layer Training and Validation accuracy indicates figure 7.

4.1 Classification

The Classifier layer is the last step of the model that predicts the class name for the labels generated by the input boxes. In this paper, this paper compare and learn the same model with another example of a AlexNet and ResNet, which is a type of classification algorithm. This paper compare the speed of the model and the method AlexNet and ResNet to determine the detection speed of the proposed model and compare the model and AlexNet and ResNet against the benchmark dataset and the self-annotated dataset.

When scale the video frame to a smaller size, the detection speed increases. For real-time 30 FPS detection, this paper achieved it with a resolution of 320x320. In this study, try to calculate the mAP for this model. The first one is the object detection IOU>0.5, which is considered as TP.

Classification of high risk of glaucoma has identified through a Shape finding classifier algorithm. Every classification is cropped in the shape of an ellipse through a curved structure. The proposed algorithm to create a screening test method to support user make a more precise diagnosis by inhibiting abnormal eye from being passed over in figure 8.

This work will also ensure that the constraints are built into the models prior to their image preparation. This means that the image that could help prepare an image for training is not available to us. This paper will use 70% train and 30% split of the data.

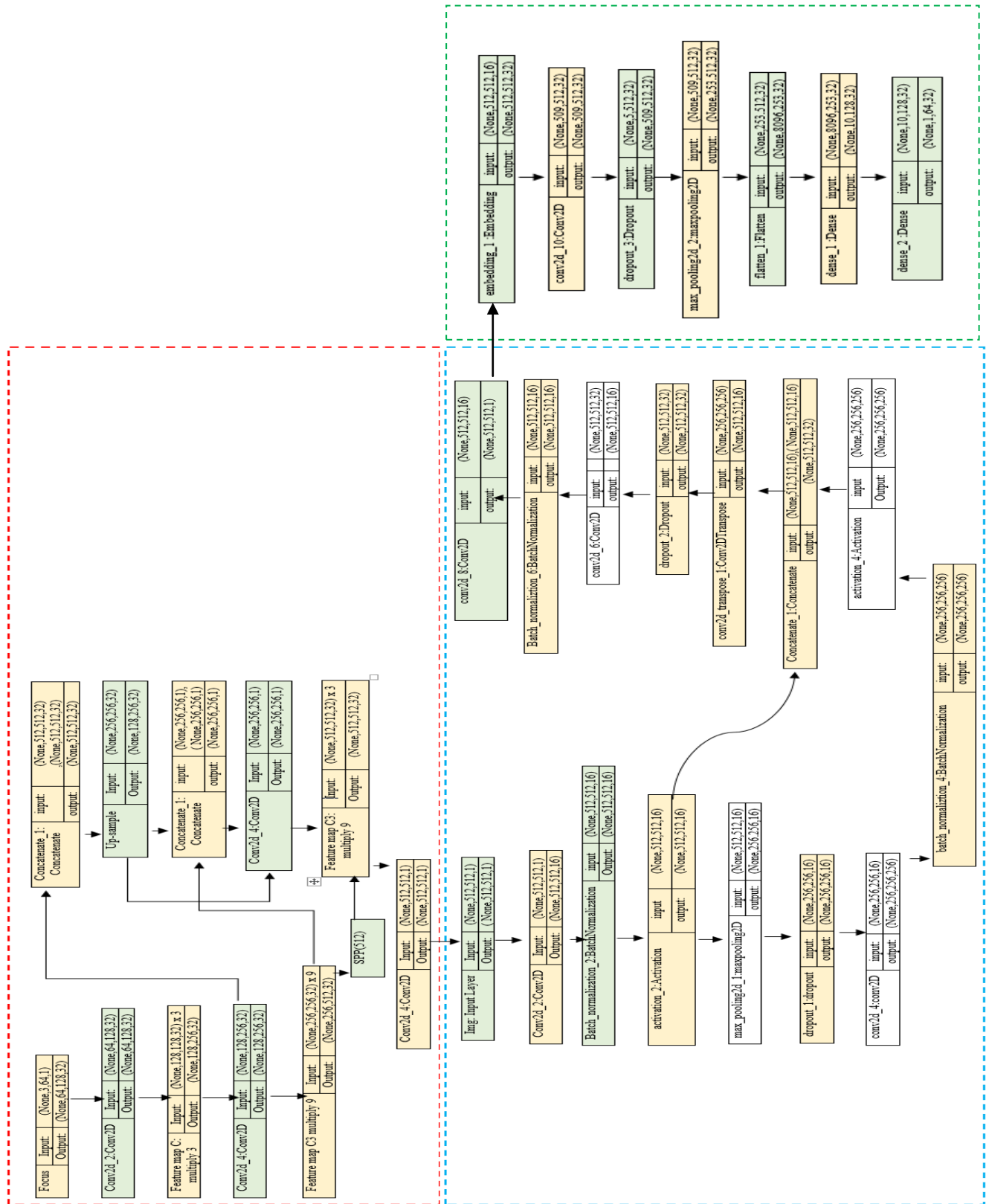


Fig 6. Functional model of Improved Y-UNet model



Layer (type)	Output Shape	Parameter #	Connected to
input_1 (InputLayer)	(None, 512)	0	
input_2 (InputLayer)	(None, 512)	0	
embedding_1 (Embedding)	(None, 512, 100)	652	input_1[0][0]
embedding_2 (Embedding)	(None, 512, 100)	652	input_2[0][0]
conv1d_1 (Conv1D)	(None, 509, 32)	64	embedding_1[0][0]
conv1d_2 (Conv1D)	(None, 507, 32)	32	embedding_2[0][0]
dropout_1 (Dropout)	(None, 509, 32)	0	conv1d_1[0][0]
dropout_2 (Dropout)	(None, 507, 32)	0	conv1d_2[0][0]
max_pooling1d_1:(MaxPooling1D)	(None, 253, 32)	0	dropout_1[0][0]
max_pooling1d_2:(MaxPooling1D)	(None, 252, 32)	0	dropout_2[0][0]
flatten_1 (Flatten)	(None, 8096)	0	max_pooling1d_1[0][0]
flatten_2 (Flatten)	(None, 8064)	0	max_pooling1d_2[0][0]
concatenate_1 :(Concatenate)	(None, 16160)	0	flatten_1[0][0] flatten_2[0][0]
dense_1 (Dense)	(None, 10)	16170	concatenate_1[0][0]
dense_2 (Dense)	(None, 1)	11	dense_1[0][0]

Total params: 652

Trainable params: 65

Non-trainable params: 0

```

Epoch 6/10
180/180 [=====] - 30s - loss: 9.9093e-04 - acc: 1.0000
Epoch 7/10
180/180 [=====] - 29s - loss: 5.1899e-04 - acc: 1.0000
Epoch 8/10
180/180 [=====] - 28s - loss: 3.7958e-04 - acc: 1.0000
Epoch 9/10
180/180 [=====] - 29s - loss: 3.0534e-04 - acc: 1.0000
Epoch 10/10
180/180 [=====] - 29s - loss: 2.6234e-04 - acc: 1.0000
    
```

Max image length: 512

Image size: 652 (180, 512) (54, 1380)

Train Accuracy: 100.000000

Test Accuracy: 99.200000



Fig.7. Performance of improved Y-UNet model layer Training and Validation accuracy

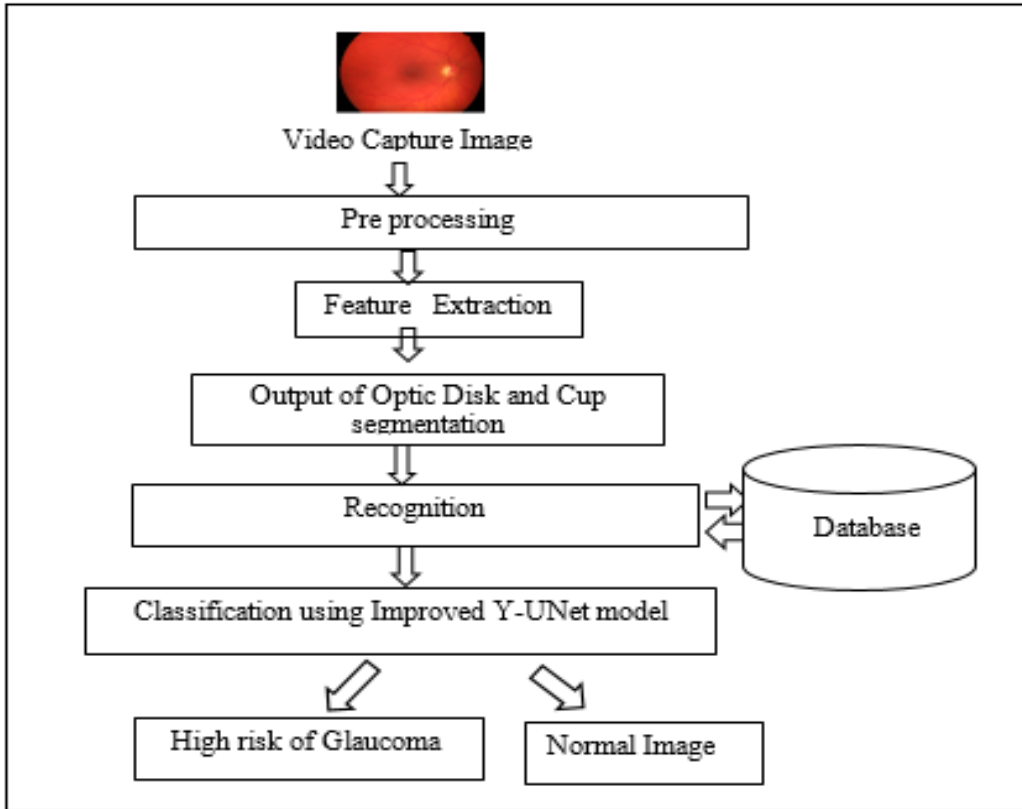


Fig 8. Classification of high risk of glaucoma disease

A shape finding algorithm has been used to identify high-risk individuals with glaucoma. Every classification is presented in the shape of an ellipse. The goal of this algorithm is to create a more precise screening test for people with glaucoma. This work will also help prepare models that are used for image preparation. This thesis aims to use 70% and 30% of the data collected for training.



SHAPE FINDING ALGORITHM

- Step 1 Pre-processing of image includes resizing the image into fixed 100px X 100px size using super intensity pixel generation.
- Step 2 Cropping image with given centroid as centered to become only Retinal area
- Step 3 Noise removing to clear the region of Interest
- Step 4 Finding center pixel of Optic Cup by using pixel intensity
- Step 5 Cropping image again to location centered pixel of Optic Disc at the retinal fundus image
- Step 6 Generating of super pixel intensity of cup as a Feature
- Step 7 Eliminating retina blood vessel using Morphological operation
- Step 8 Disc boundary smoothing using ellipse fitting
- Step 9 Segmenting of Optic Disk and Cup using Color Thresholding
- Step 10 Finding shape of disc and cup based Region based Convolutional Neural Network
- Step 11 Evaluating cup to disc ratio
- Step 12 Classification of the fundus image into high risky of glaucoma or healthy.

4.2 Evaluation of Cup-to-Disc Ratio

A fitting ellipse is executed to smooth the segmented framework [21]. This method calculates an ellipse around all the pixels of a segmented outline in figure 9. The sum of the square off from the centroid to each pixel is then computed.

$$\text{Disc and Cup area distance} = \sqrt{(p - p_i)^2 + (q - q_j)^2} \tag{20}$$

The SMART technology helps in estimating the disc and cup functional boundaries, which are also known as ONH. It also displays better information about the cup-to-disc ratio [22] and vertical and horizontal cup to disc area ratios [24]. The proposed method has given highest F1 score for disk and cup [25].

$$\text{Vertical cup-to-disc ratio } CDR_v = \frac{v_d}{v_c} \tag{21}$$

Here, v_d implies vertical disk; v_c implies vertical cup. Then will be compute vertical CDR.

$$\text{Horizontal cup-to-disc ratio } = CDR_h = \frac{h_d}{h_c} \tag{22}$$

Here, h_d implies horizontal disk; h_c implies horizontal cup. Then will be compute horizontal CDR. Evaluation measurements shows in table 1.

Here compute accurate area of ONH equation given below,

$$ONH_{area}(mm^2) = \left(\pi \frac{r}{4}\right) \times h_{cdr}(mm) \times v_{cdr}(mm) \tag{23}$$

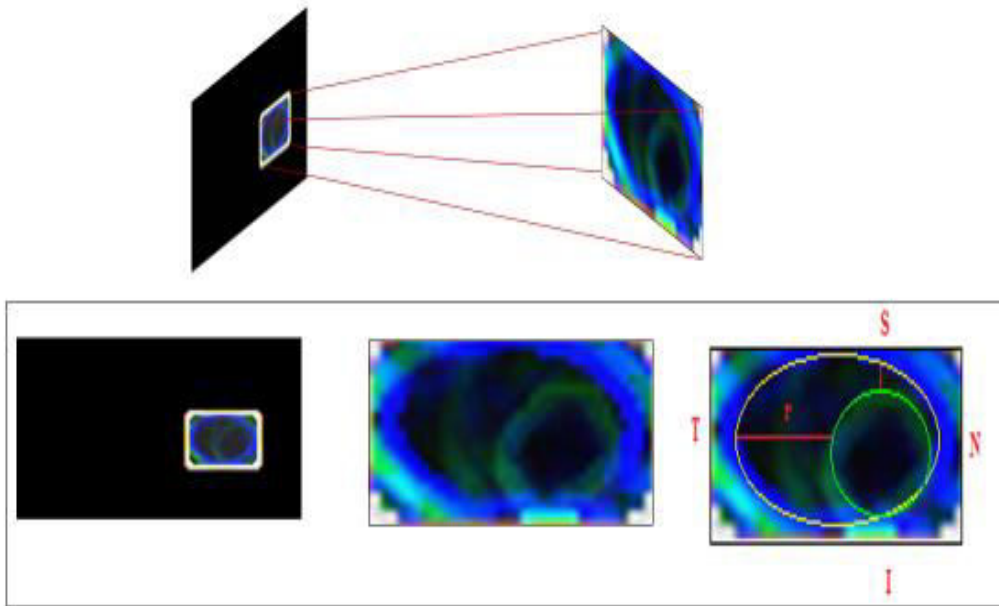


Fig.9 Segmentation of Optic Cup and Disc for Evaluation

In figure 10, after the cup to disc evaluation process disc and cup areas are identified. Then Vertical & Horizontal CDR ratio is evaluated and finally it is checked with ISNT rule. In this research contribution, additionally applied overlap tile

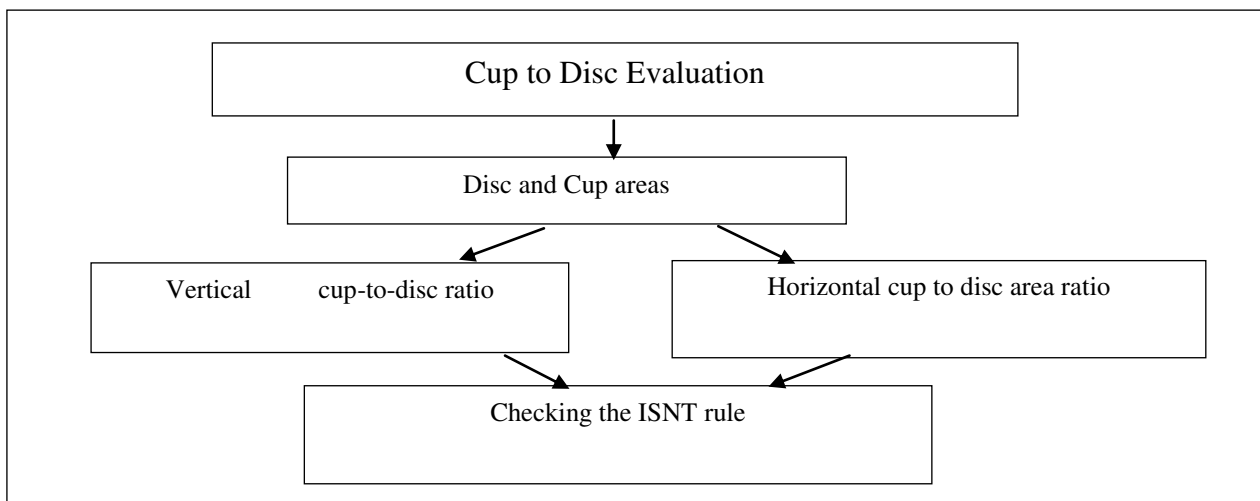


Fig. 10 Evaluation of Cup to Disk ratio

technique for validation which made it conceivable to segment high resolution with overall precision 99.1%.

V. EXPERIMENTAL RESULTS AND DISCUSSION*

5.1. Dataset

The Classifier layer is the last component of the model that is used to predict the name of the class for the input label and the regression of the box in figure 9. The proposed method used patches of a size 32*32 pixel to find the region based CNN image. This patch collection consists of 190,000 patches.



This research are collected by arbitrarily separating 8,500 patches in every single dataset training image. The dataset consists of over 171,000 patches. The majority of the patches are used for training and testing. Comparison of mAP and speed for Improved Y-UNet model from existing model in table 2 and figure 11 shows graphical representation of this model.

Table 1. Evaluation measurements for finding Glaucoma suspects

Image	Center x	Center y	Vessel x	Vessel y	Disk diameter <i>mm</i>	ONH area <i>mm²</i>	result of CDR <i>CDR_r</i>	Glaucoma suspect
1	860	1180	771	1193	385	3.17	0.18	1
2	2715	1070	2773	1096	365	3.09	0.19	0
3	2648	1155	2694	1178	402	3.24	0.16	1
4	2759	965	2808	1168	369	3.10	0.24	1
5	873	1107	828	1128	372	3.12	0.22	1
6	988	1085	907	1086	416	3.30	0.24	1
7	900	1050	887	1055	376	3.13	0.18	1
8	2647	1176	2718	1152	430	3.35	0.22	1
9	2703	1153	2726	1180	424	3.33	0.21	1
10	2768	1278	2789	1283	368	3.10	0.18	1
11	990	1094	946	1095	393	3.20	0.19	1
12	966	1122	939	1125	414	3.29	0.19	1
13	984	1160	928	1173	331	2.94	0.19	0
14	2748	1074	2812	1086	374	3.13	0.17	1
15	2684	1074	2764	1119	426	3.34	0.21	1
16	2638	1108	2681	1080	368	3.10	0.23	1
17	941	1159	887	1169	391	3.20	0.24	1
18	933	1116	871	1138	373	3.12	0.21	1
19	888	1078	867	1077	394	3.21	0.19	1

Table 2. Comparison of mAP and speed for improved Y-UNet model from existing Model

Method	ResNet	AlexNet	Improved Y-UNet
mAP (%)	36.2	67.9	84.9
Runtime (sec/img)	0.82	0.26	0.09

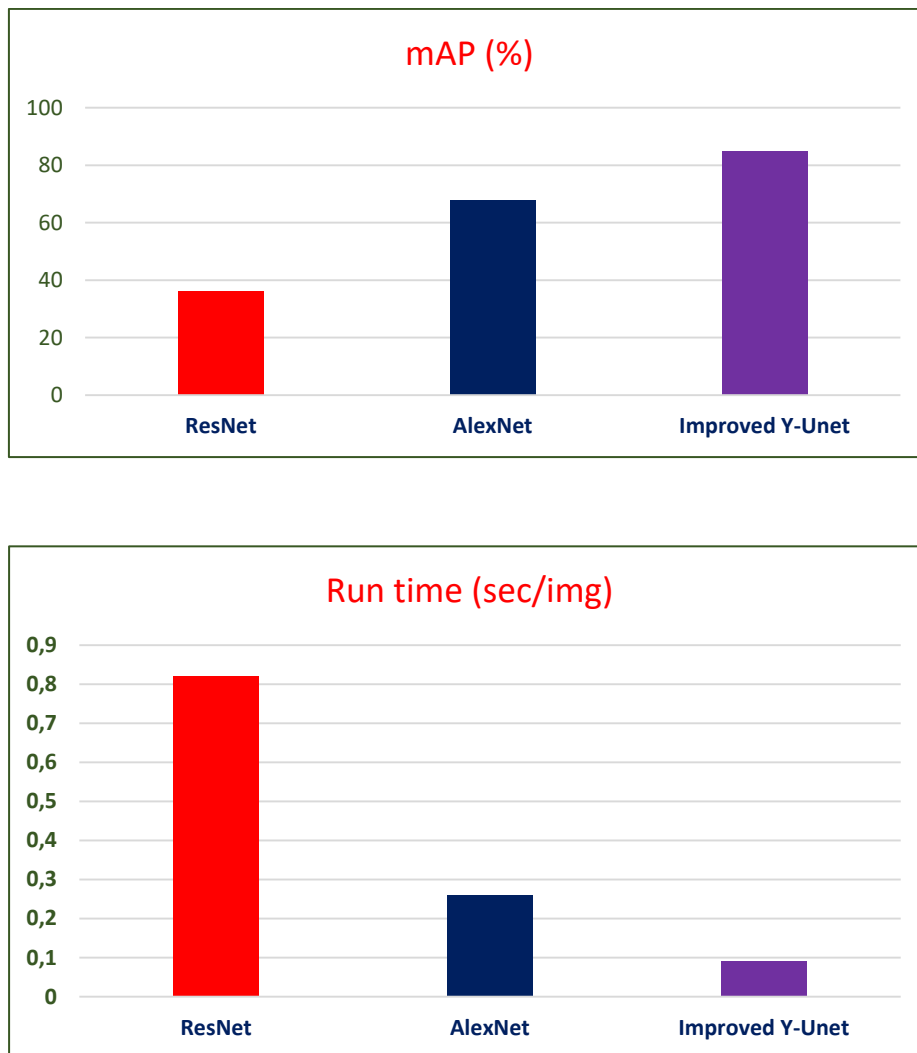


Fig 11.. Graphical representation of mAP and Runtime performance for Improved Y-UNet model from existing model

VI. CONCLUSION

In this research, combine the output of a segmentation model with a classification model. This paper achieved better performance against the models that are used for the classification of the retinal fundus image. The proposed Improved Y-UNet finding may help identify people with suspected glaucoma. It could also reveal the disease development and provide predictive evaluation. The disc to cup ratio is one of the important factors that can be used to identify the glaucoma disease. This paper proposed a method that uses whole image classifiers to improve the accuracy and sensitivity of the test.

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