Early Detection of Glaucoma using Modified Residual U-Net Convolutional Neural Network

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Abstract

Glaucoma is the second leading cause of blindness all over the world, with apparently 75 million cases reported worldwide in 2018. If it's not diagnosed at an early stage, glaucoma may cause irreversible damage to the optic nerve which results in blindness. The Optic head examination is the widely used structured diagnosis approach in the current medical field for Glaucoma detection which involves measuring the Optic Cup-to-Disc ratio from the fundus image. Estimation of Optic Cup-to-Disc requires accurate segmentation of the Optic Cup and Optic Disc from the fundus which is a tedious and time-consuming task even for the experienced ophthalmologist. This thesis addresses the challenge by using the Residual blocks and deep learning segmentation network (Encode-Decoder Network) to form a model called Modified Residual U-Net Convolutional Neural Network (Res U-Net) for automatic segmentation of Optic Cup and Optic Disc. Our experiments include the comparison of various methods on the publicly available dataset like DRIONS-DB and RIMONE V3. For Optic Cup and Optic Disc segmentation, my method performs competitively compared to the other techniques in terms of quality of recognition.

Keywords: Optic Cup-to-Disc segmentation, Modified Res U-Net, deep learning segmentation network, glaucoma detection, and fundus image.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Table Page

LIST OF SYMBOLS

CDR	**Cup-to-disc Ratio**
TP	**True Positive**
FP	**False Positive**
FN	**False Negative**
TPR	**True Positive Ratio**
TNR	**True Negative Ratio**
DFI	**Digital Fundus Image**
ROC	**Region of Curve**
CLAHE	**Contrast Limited Adaptive Histogram Equalizer**
ROI	**Region of Interest**
RELU	**Rectified Linear Unit**
IOU	**Intersection over Union**

Chapter 1

Introduction

Glaucoma is the second leading cause of blindness in the world, with apparently 75 million cases in 2020 and it is expected to increase by 30 million in 2040 according to [1,2]. Glaucoma can be broadly classified into two categories: Open Angle Glaucoma and Closed Angular Glaucoma. Among them, Open-Angle Glaucoma has more number of registered cases all over the world and has no symptoms. Open-Angle Glaucoma is a chronic Eye disease which is caused due to the blockage in the flow of liquid called Aqueous humor. Aqueous humor flows inside the eye directly below the optic nerve and keeps the eye pressure low. The blockage in the eye creates an accumulation of the liquid and destroys the optic nerve which carries the information to the brain. When information from the eye to the brain is lost it results in permanent blindness. In the current medical field, glaucoma does not have any permanent solution, so early detection is the only possibility. Due to its risk of spreading and diagnosis complexity, my research mainly focuses on addressing the glaucoma diagnosis. **Figure 1** shows the difference between the normal eye and the Glaucoma eye (Open Angle Glaucoma).

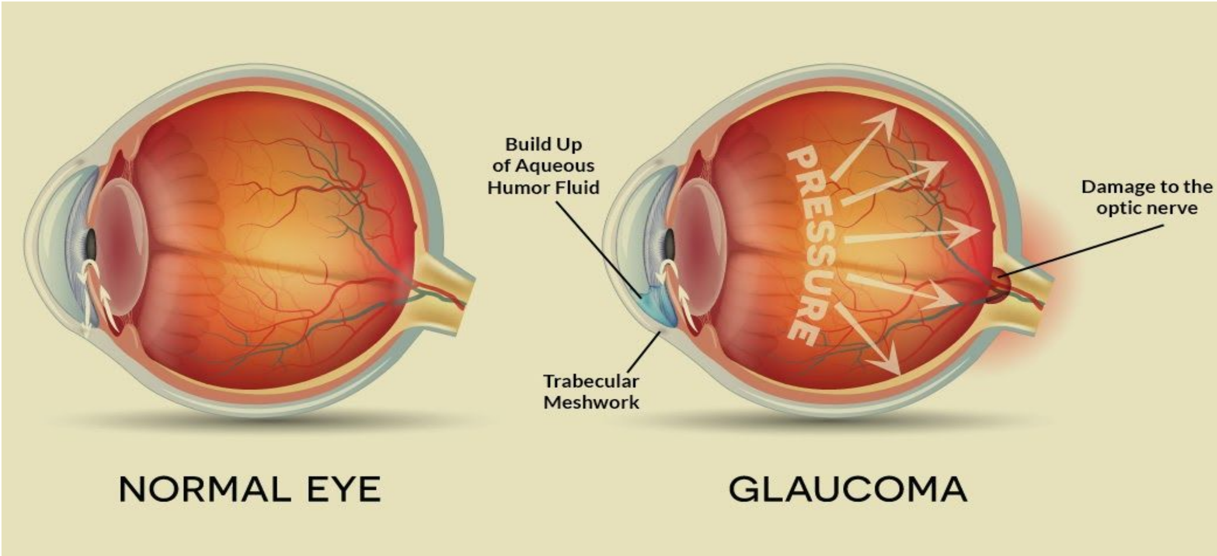
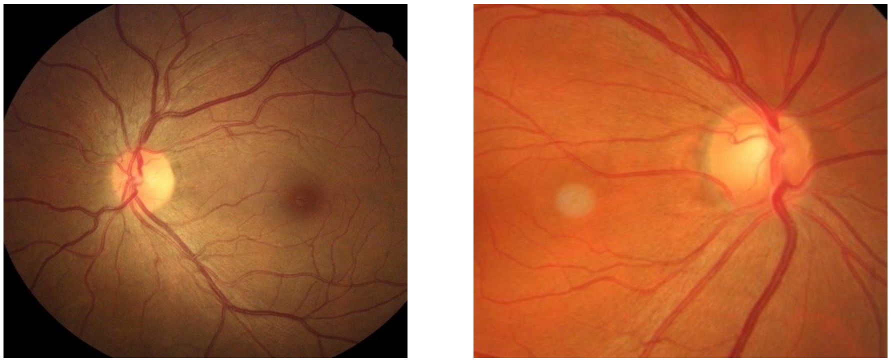


Fig 2.1: Difference between the Normal Eye and Glaucoma affected Eye

To detect glaucoma at an early stage, the patient is subjected to a variety of tests like Field Examination, Optic head examination, and Pressure Checkup. Among which Optic head Examination is the most reliable and efficient method for detecting the presence of glaucoma due to its cost-effectiveness and simple structure. In the Optic Head Examination, the doctor takes a picture of the human eye structure in the form of a Fundus image (Medical image containing information about eye structure) using a Fundus Camera. Then the doctor tries to estimate the boundaries of the Optic Disc and Optic Cup to calculate the Optic Cup-to-Disc ratio to predict whether a patient has Glaucoma or not. Below **Figure 2** shows the visual representation of the Fundus image and Optic Disc and Optic Cup boundaries.



Non-Glaucoma Fundus image Glaucoma Fundus Image

Fig 2.2 (a): Example Fundus image of both Glaucoma eye and normal eye

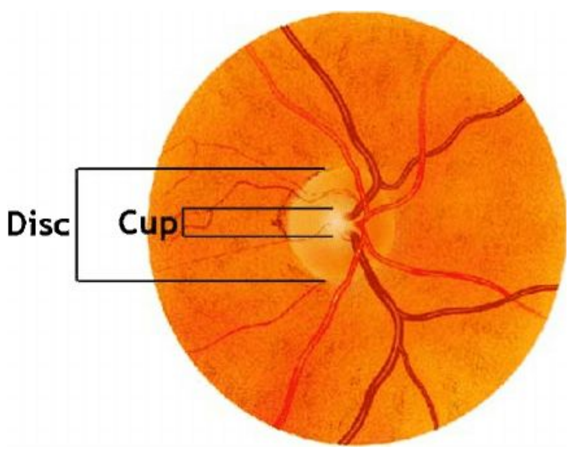


Fig 2.2 (b): Example of Optic Disc and Cup labeled in a Fundus image

Predicting the boundaries of the Optic Disc and Optic Cup accurately is an important requirement for detecting the presence of Glaucoma which is a difficult task for human graders and experienced ophthalmologists. There are several approaches available in the field of computer vision and deep learning for automatic segmentation of the Optic Cup and Disc. The first approach is to determine the boundaries of the optic cup and optic disc using convolution filters in the deep Convolutional Neural Network model. And the drawbacks of this technique are not good at recognizing the weak neuroretinal rim edge of the optic cup when the optic cup-to-disc is so small and also not good with low contrast images. Another approach involves the segmentation of optic cup and optic disc using some morphological operation or using deformable energy-based models. And drawback of this approach is it is not good at recognizing the weak rim edge of the optic cup and it also requires proper initialization like a bounding box around the optic cup and optic disc for segmentation. My method addresses these issues by using a semantic segmentation network along with residual blocks that do not require any sort of bounding box initialization and it also overcomes the issue of recognizing the neuroretinal rim edge of both the Optic Cup and Disc by classifying each pixel in an image. Figure 3 shows an example of noisy and irregular contrast fundus images.

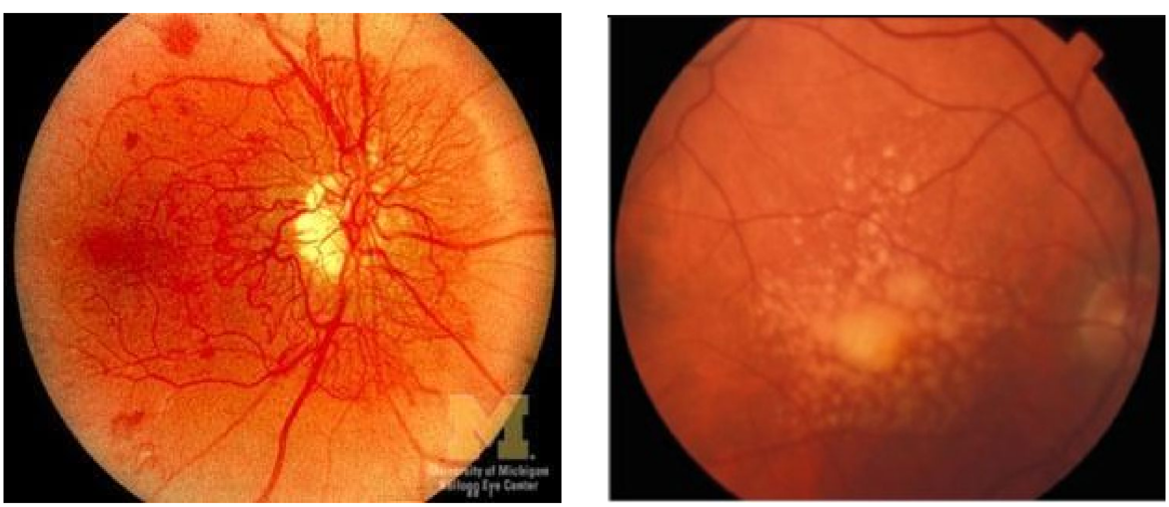


Fig 2.3 (a): Noisy Fundus image **Fig 2.3 (b): Irregular contrast image**

My proposed method detects the boundaries of Optic Disc and Cup very precisely compared to other methods. And it also helps doctors in detecting glaucoma at an early stage even for the low contrast images and noisy fundus images.

Chapter 2

Related Works

In this section, we give an overview of several methods for optic cup and disc segmentation which have been evaluated by their authors on publicly available datasets with both images and ground truth provided.

For Optic Disc segmentation, the author of [3] uses a Fully Convolutional Neural network along with an “inception” module from GoogleNet [4]. The author of paper [3] addresses the issue of detecting the boundaries of Optic Disc by segmenting the retinal nerve and optic disc using a Fully Convolutional Network. The Architecture consists of multiple convolutional layers, pooling layers, and inception modules for generating optic Disc and retinal nerve segmentation maps. Let’s briefly look at architecture developed by the author of Paper [3]. Figure 4 shows the Architecture and different modules in it.

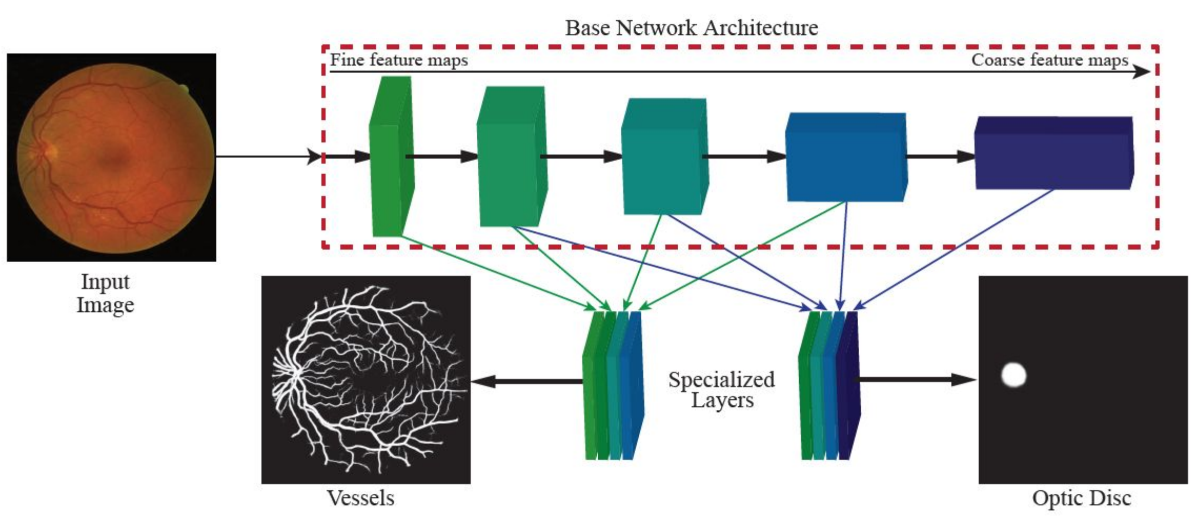


Fig 2.4: Overview of CNN Architecture by Paper [3]

The above CNN Architecture draws inspiration from the VGG net [5] and the inception module concept from GoogleNet [4]. The architecture consists of a base network and specialized layers. The Base network consists of a series of convolutional layers with different filter sizes along with the REctified Linear Unit (RELU) Activation Function. And these convolutional layers are followed by max-pooling layers to downsample the input image when we go further deep into the network so the model retains only the necessary information. There are two specialized layers one for generating an optic nerve segmentation map and the other for generating an optic disc segmentation map. The specialized layers are formed by the input feature map from the convolutional layers of the base network based on the inception module concept.

The specialized layer which generates the optic nerve segmentation map takes the input feature from the first four layers because when the input goes further deep into the network only the coarser information is retrained. So other information like small retinal nerves is removed from features maps. The feature maps from each convolutional layer are then resized to image size and are concatenated to the final layers of each stage to form a retinal nerve segmentation map. In the same way, the features maps from the last four layers are resized to image size and concatenated to form a segmentation map containing the optic disc information. The majority of the convolutional layers employ 3x3 convolutional filters for efficiency except the ones used for combining the output (1x1 filter).

The model uses a class-balancing cross-entropy loss function for the training network. The loss function is defined as:

$$\mathcal{L}(\mathbf{W}) = -\beta \sum_{j \in Y_+} \log P(y_j = 1 | X; \mathbf{W}) - (1-\beta) \sum_{j \in Y_-} \log P(y_j = 0 | X; \mathbf{W})$$

The Advantage of this architecture compared to the other methods which use morphological techniques or energy-based models is that it produces better results in the segmentation of optic disc from the digital fundus image. And the current model does not require any form of initialization in the success segmentation of optic disc. And also requires less time for training the model.

The Disadvantage of this architecture is that it only addresses the issue of extracting the optic disc from the digital fundus image whereas it fails to address the issue of extraction of the optic cup which is difficult and necessary information to predict the presence of glaucoma in the fundus image.

The author of the paper [5] addresses the issue of detecting the optic cup and optic disc from the fundus image using a Deep Convolutional Neural Network. In this paper, the author detects the boundaries of both optic cup and disc from the Digital Fundus Image (DFI). The input Fundus image is first pre-processed before it is given to the model. The pre-processing step involves finding the ROI (Optic Disc and Optic Cup) in the fundus image by dividing the image into grids and locating the region of more brightest pixel values in the fundus image. Figure 5 shows the Architecture of the paper [5].

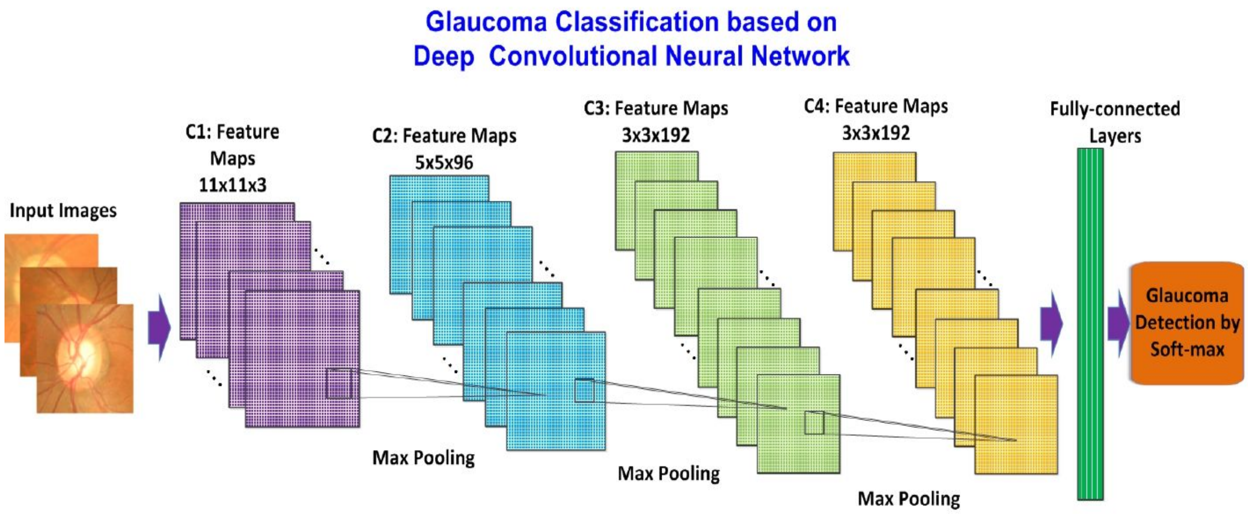


Fig 2.5: CNN Architecture of Paper [5]

After detecting the region of brightest pixels in the fundus image. We have successfully extracted the ROI which is optic Disc and optic cup from the image. Then we resize the image into 256x256 pixel size to make the model trainer faster. After resizing the image into 256x256 size we give the image to the model as an input. The CNN architecture proposed in Paper [5] consisting of 4 layers. Each layer has 5 convolutional blocks followed by the max-pooling operation. The final layer is a dense layer with a softmax activation function for classifying whether the given image has Glaucoma or not. The model used (ROC) Region under the Curve has the evaluation metric to evaluate the performance of the model. The ROC is plotted to show the tradeoff between the sensitivity TPR (True Positive Rate) and specificity TNR (True Negative Rate), defined as:

$$TPR = \frac{TP}{TP+FN},\ TNR = \frac{TN}{TN+FP},$$

Where TP and TN are the number of True Positives and True Negatives respectively, and FP and FN are the numbers of False Positive and False Negative respectively.

The advantage of this model compared to the previous model in the paper [3] is that it addresses the issue of detecting both optic disc and optic cup whereas the paper [3] only tries to segment the optic disc, not the optic cup. And the current method preprocessing makes it easier for the model to detect the Optic Cup and Optic Disc efficient compared to the previous method. Moreover, this model takes less time to train the model compared to the previous method including the manual segmentation by the human graders and ophthalmologists.

The Disadvantage of this model is that it is not efficient with the noisy and high contrast fundus images. The noisy fundus image is a common problem in the current medical field due to the improper placement of the patient eye next to the fundus camera (imaging device for capturing human eye structure). The preprocessing step in this paper cannot locate the ROI in the fundus image if it contains noise on the neuroretinal rim of the Optic Disc. Instead, the method will localize the edge of the retinal rim which is not a region of interest for Glaucoma detection. Moreover, the model is also not good at recognizing the critical stage of Glaucoma due to the less distance between the Optic Cup and Optic Disc. Which is a necessary case the model needs to handle because they are the person who is at risk of blindness if not treated soon.

The Convolutional Neural Network is really good at many problems but in the case of Glaucoma detection, it was not efficient in recognizing the critical stages of Glaucoma. So let's move to the Semantic Segmentation model which is most commonly used for the Bio-Medical diagnosis. In which we will classify each pixel based on the class it belongs to and produces the segmentation map (probability map) which precisely segments the Optic Disc and Optic cup from the Digital Fundus image compared to the method provided in paper [3].

The author of the paper [6] uses one of the Semantic Segmentation models called the U-Net Convolutional Neural Network for the segmentation of the Optic Disc and Optic Cup. In this paper, the author uses a preprocessing step to remove the contrast in the Digital fundus image by using CLAHE (Contrast Limited Adaptive Histogram Equalizer) before giving it to the U-Net Architecture. In the preprocessing step the fundus images are resized to 128x128 pixel size. After Resizing the fundus image it's divided into small tiles and is equalized parallel by changing the color of image regions. After equalizing each tile in the images are combined using the bilinear interpolation technique. Below **Figure 6** shows the pipeline for extracting the Optic Disc from the Fundus image.

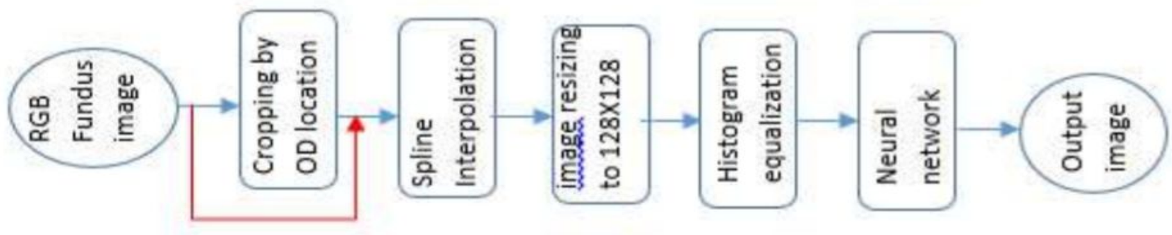


Fig 2.6: Pipeline of the Proposed method for the task of Optic Disc segmentation

For Optic Cup segmentation, the author uses the same pipeline that was used for the Optic Disc segmentation task. After preprocessing the fundus image we give the cropped fundus image for the segmentation of the Optic Cup as an input to the U-Net Architecture. And for the Optic Disc segmentation, we provide the image as it is. **Figure 7** shows the Architecture of the U-Net Architecture.

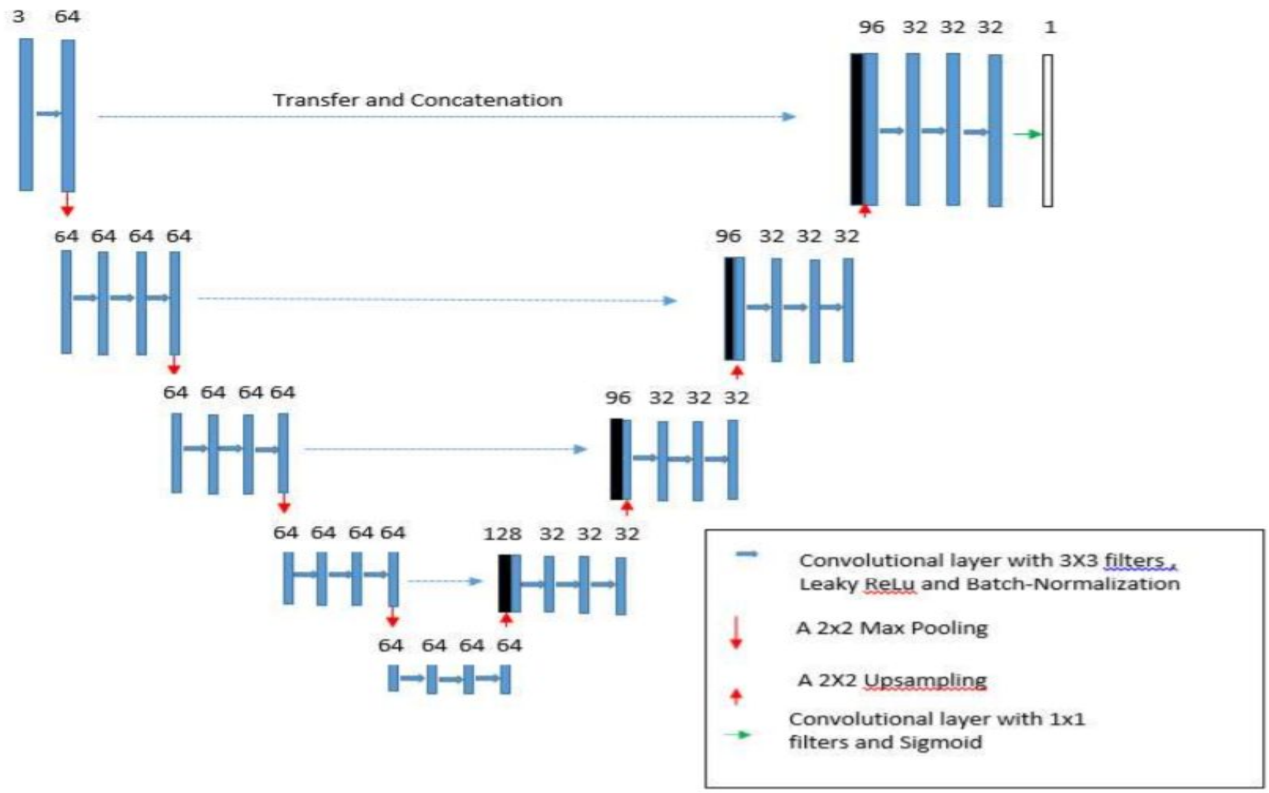


Fig 2.7: Proposed U-Net Architecture by the paper[6]

The U-Net Architecture consists of two paths: Contracting path and Expanding path. The Contracting path consists of Fully Convolutional layers except for the dense layer. In the contracting path, the preprocessed image is passed through the series of convolutional blocks with no filters on top of every block as shown in the above **Figure 7.** The image is downsampled by the stride of 2 on end every layer so that model has less parameter to train on and only necessary information is passed to the next layer after downsampling. So it will be easy for the model to detect what content is present on the image. And in the expanding path, we have the same series of convolutional blocks along with concatenation of the feature map from the same layers contracting path. This concatenation helps the model to learn where the information is located. After the concatenation, the image is upsampled by stride 2. Which provides the up-sampled high-resolution image with the pixel being classified. The model uses log dice loss as one of the metrics to evaluate the performance of the model. The loss function is:

$$C(X,Y) = -\log f(X,Y) \tag{1}$$

$$f(X,Y) = \frac{2\sum_{i,j}^{h,w} x_{i,j} y_{i,j}}{\sum_{i,j}^{h,w} x_{i,j}^2 + \sum_{i,j}^{h,w} y_{i,j}^2} \tag{2}$$

Where the probability that the pixels predicted is for the foreground is $X = (x_{i,j})$ and the given output is $Y = (y_{i,j})$, h and w is the height and width respectively.

The advantages of the paper [6] compared to previous papers [5] and [3] is that it uses a semantic segmentation network which classifies each pixel in the image based on the class type it belongs to (class type: optic cup, optic disc, and background). And it also generates better segmentation results for both optic disc and cup compared to the method [3] and [5]. The author of the paper [6] detects the presence of glaucoma from the segmentation map by dividing the no of white pixels in the optic cup segmentation map by the no of white pixels in the optic disc segmentation map. Using the threshold for glaucoma condition we can classify whether that image has glaucoma or not. And the threshold limit for classifying glaucoma is 0.75

The Disadvantage of the paper [6] is that the model is not quite deep so it cannot segment the result better from the fundus image compared to other segmentation networks. And the model cannot be able to extract the optic cup from the fundus because of the smaller optic cup region in the fundus image.

The author of the paper [8] uses a variant of semantic segmentation along with residual blocks to perform segmentation tasks. In this paper, the author does not use any preprocessing step for the optic disc segmentation task and still, he achieves better results in terms of recognition compared to the paper [8]. For optic cup segmentation, the author crops the fundus image along the area of the optic disc before giving it to the model. Below **Figure 8** shows the Residual U-Net Architecture.

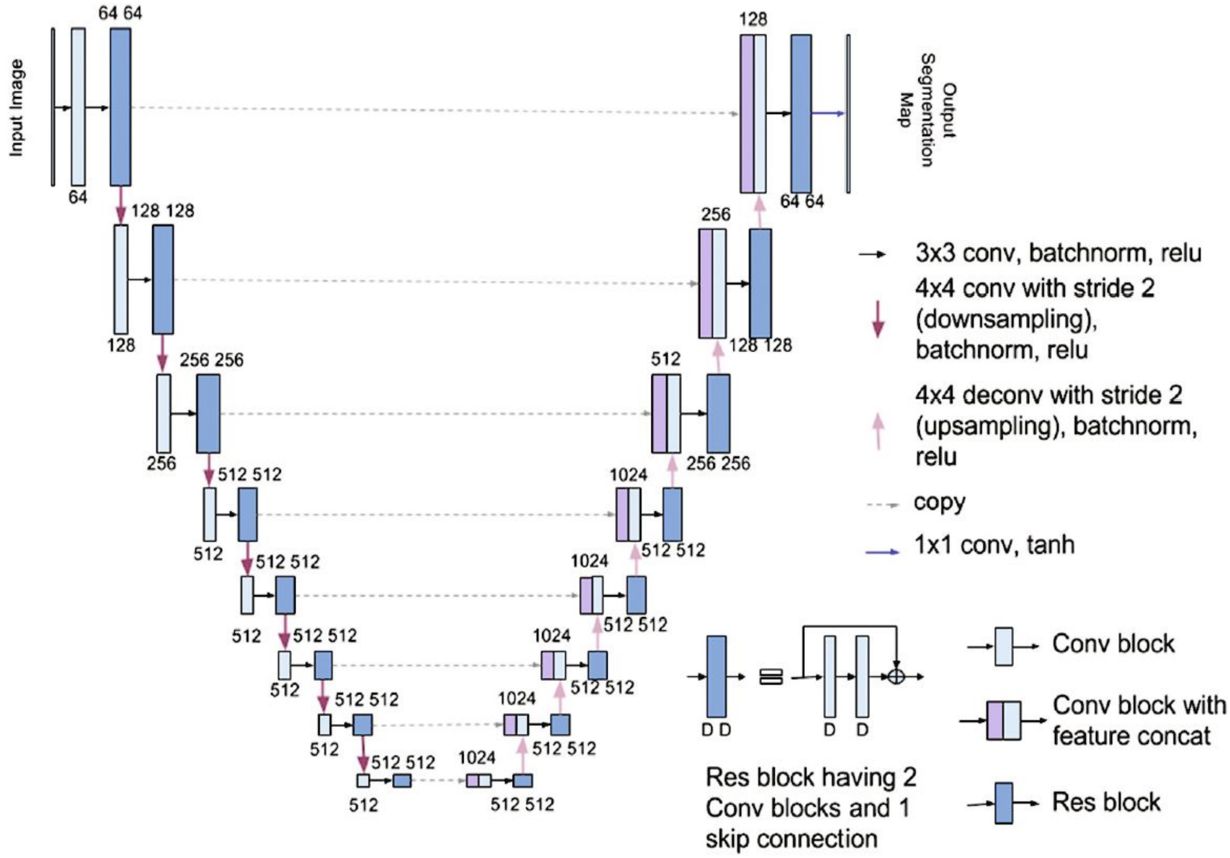
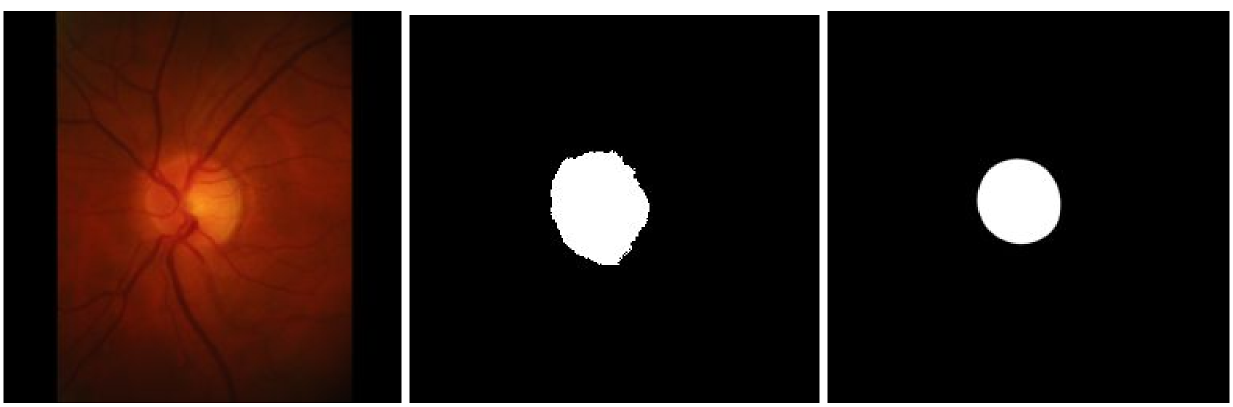


Figure 2.8: Proposed Residual U-Net Architecture by the Paper [8]

The above diagram consists of U-Net Architecture along with Residual blocks instead of Convolution blocks. A Residual block contains two convolution blocks with a 3x3 filter size and a skip connection. The above architecture consists of a convolution block followed by a residual block at each layer. And then images are downsampled using a convolution block with 4x4 filter size and stride by 2, batch normalization, and a ReLU activation function at the end of each layer. Then images are upsampled to localize the feature in the fundus image by using a Transposed convolution with 4x4 filter size and stride by 2, batch normalization, and ReLU Activation function.

The advantages of the Current model compared to the previous model in the paper [7] are the Residual blocks and a deeper architecture. The U-Net Architecture has a concatenation feature (or long Skip Connection) which helps the model to perform better when the model is narrow but when we go deeper it is not good at segmenting features from the fundus image. The Residual blocks short skip connection helps the model to perform better even in deeper layers.

The disadvantage of the Res U-net is that it is not good at recognizing high contrast images and still the predicted segmentation results are not pretty close compared to the correct segmentation map. This may lead to the wrong diagnosis of Glaucoma. The segmentation results produced by this model are shown in **Figure 9** below.



Input Fundus Image **Predicted Segmentation map** **Correct Segmentation map**

Figure 2.9: Example comparison between Predicted and Correct segmentation map by Res U-Net Architecture

Chapter 3

Proposed Method

In this section, we give an overview of my proposed method in detail. And also we are going to give in-depth details about how the proposed model works and how my proposed solution is efficiently going to address the issues faced by the previous methods we saw in the related works.

In the proposed method, I have used preprocessing steps for both the optic cup and optic disc segmentation before giving it to the model. Let's see the preprocessing pipeline for segmenting optic disc and cup from the digital Fundus Image. Below **Figure 10** shows the pipeline for segmenting the optic disc from the fundus image.

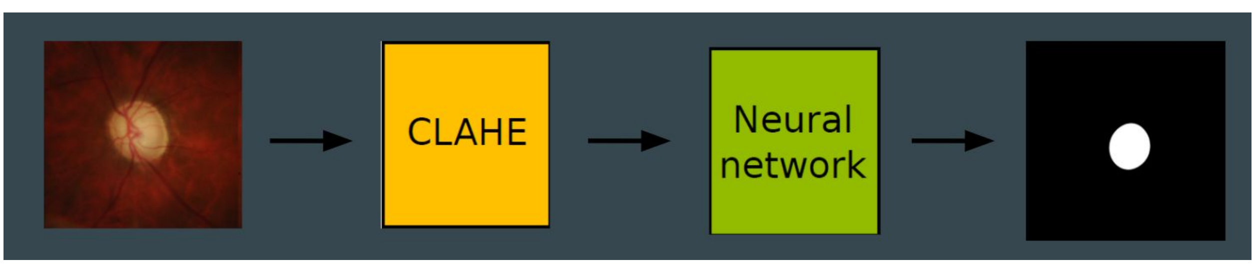


Figure 2.10: Pipeline for segmentation optic disc from the digital fundus image

In the above Figure, we take a digital fundus image and give it to the CLAHE module. CLAHE stands for Contrast Limited Adaptive Histogram Equalizer. CLAHE is a computer vision technique it is used to remove the irregular contrast within the fundus image. In the CLAHE module, we take input fundus image (Containing noise) and generate a histogram on each patch of the images. After generating the histogram we check the skewed histogram and stretch it between the specified range to remove the excess noise on the fundus image. Below **Figure 11** shows an example process of removing noise from the fundus image.

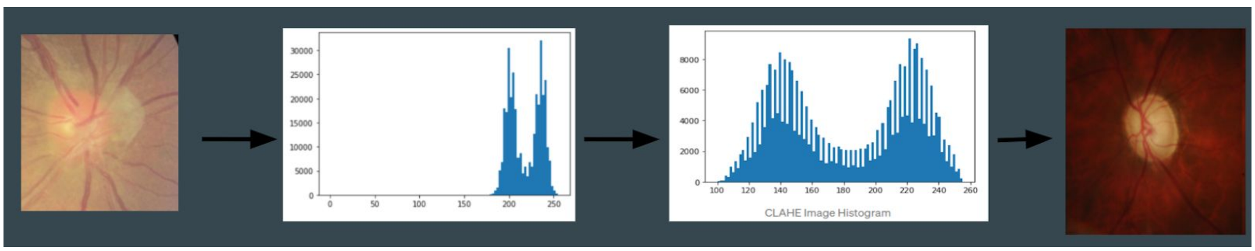


Figure 2.11: Example process of removing the extra noise from the Fundus image

After removing the irregular contrast from the image is given to the Res U-Net Convolutional neural network for optic disc segmentation. Before we see in detail the Modified Residual U-Net Architecture let us take a look at the pipeline for segmenting the optic cup from the fundus image. Below **Figure 12** shows the pipeline for segmenting the optic cup from the fundus image.

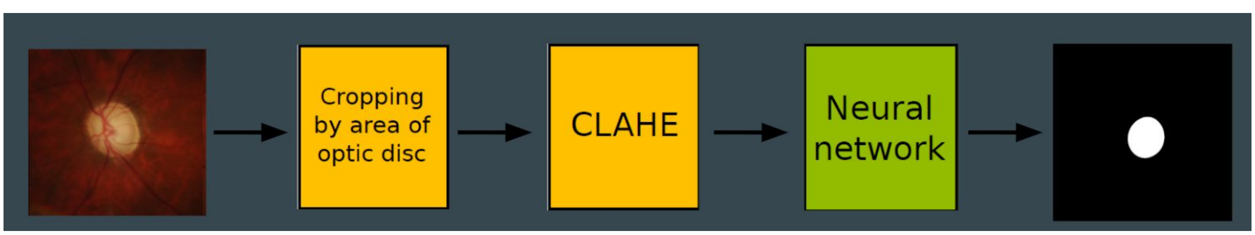


Figure 2.12: Pipeline for segmenting the optic cup from the fundus image

In the above image, we take the input fundus image and crop them along the area of the optic disc using coordinates from the publicly available datasets. After cropping we have the cropped fundus image which is given to the CLAHE module. In the CLAHE we limit the contrast by equalizing them based on the clip limit. Afterward we feed to the neural network for segmenting the optic cup from the fundus image. Now let us take a look at the proposed Architecture. Below **Figure 13** shows the proposed architecture.

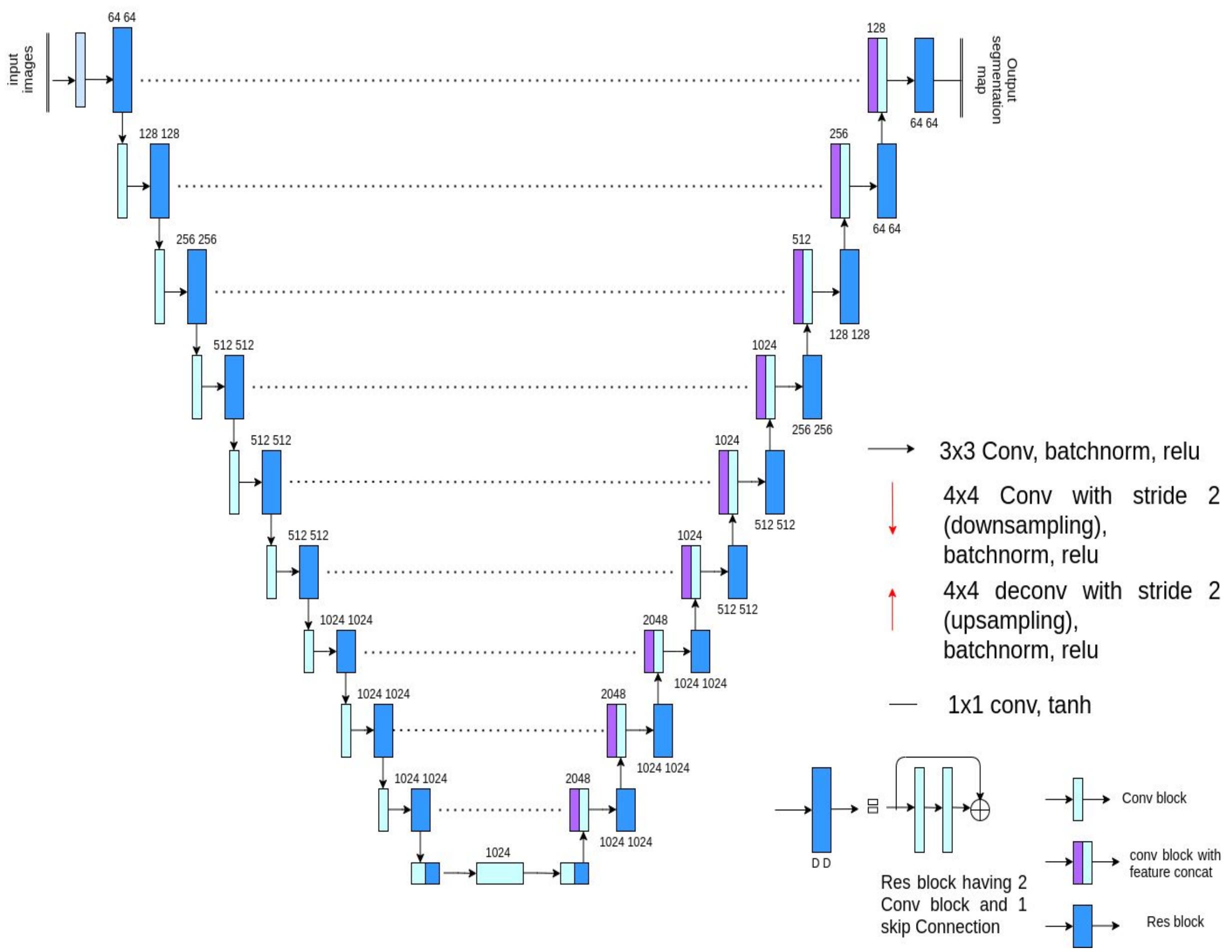


Figure 2.13: Modified Residual U-Net Architecture (My Proposed Architecture)

The above image contains a Variant of U-Net Architecture along with the residual blocks for efficiently segmenting the optic disc and cup from the fundus image. Like the original U-Net Architecture, my proposed architecture also contains a contracting path and an expanding path. The Contracting path contains Fully convolutional layers where each layer has a residual block followed by the downsampling operation using convolutional block with stride 2. The residual block contains two convolutional blocks with no filters specified on top of the blocks followed by a skip connection. At the end of each layer, we downsample the image so that the necessary information is forward to the next layer. After that, the images are upsampled to locate the ROI in the image using the deconvolutional block on the expanding path along with the concatenation of feature maps from the same layer of the contracting path. By using the concatenation of the feature map from the contracting path the model can learn the patterns efficiently and also can locate the pattern position by upsampling the image to the same size. At the end of the layer, the feature map is given to a 1x1 convolutional layer with tanh activation function to generate a probability map containing the ROI of the fundus image. We use a log dice loss to evaluate the model and it’s defined as:

$$C(X,Y) = -log f(X,Y) \tag{1}$$

$$f(X,Y) = \frac{2\sum_{i,j}^{h,w} x_{i,j} y_{i,j}}{\sum_{i,j}^{h,w} x_{i,j}^2 + \sum_{i,j}^{h,w} y_{i,j}^2} \tag{2}$$

Where the probability that the pixels predicted is for the foreground is $X = (x_{i,j})$ and the given output is $Y = (y_{i,j})$, h and w is the height and width respectively.

The advantage of my method compared to other methods in the related works is that it produces accurate results in terms of segmentation even on the noisy fundus images with the help of the CLAHE module. For the optic disc segmentation, we have a specified pipeline that helps the model in overcoming the noisy fundus image cases. Same way my proposed method contains a specified pipeline for optic cup segmentation also in which we have cropped the fundus image along the optic disc area before equalizing the contrast in the fundus image. The cropping along the area of the optic disc helps my model to segment the optic cup precisely compared to the Res U-Net Convolutional neural network.

Chapter 4

Experiments and Results

1. Datasets Used:

I have used a publicly available dataset for both training and testing purposes. The dataset I have used are:

- **RIM-ONE V3:** This dataset contains 3 folders: Healthy fundus folder and Glaucoma and Suspects fundus image. The Healthy Fundus images contain 159 stereo images, segmentation maps, and coordinates for both optic cup and optic disc for creating a bounding box. The same way the Glaucoma and suspects folder contains these items in them. Below **Figure 14** shows an example Fundus image and segmentation map from this dataset.

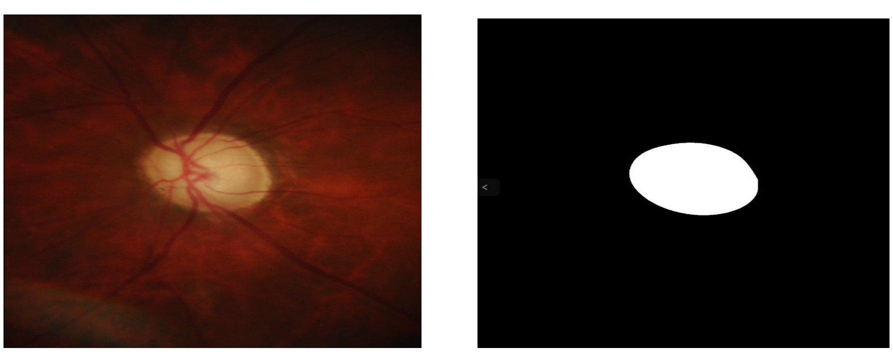


Figure 2.14: Sample fundus image and a segmentation map from the RIM-ONE V3 dataset

- **DRISHTI GS:** This dataset contains 2 folders: Test and training folders. And each test and training folder contains an images folder and a segmentation map folder. The image folder contains 50 digital fundus images which contain both Glaucoma and healthy fundus images. And the Test folder contains the 51 images along with the segmentation maps. Below **Figure 15** shows an example of a Fundus image and a segmentation map from the DRISHTI GS dataset.

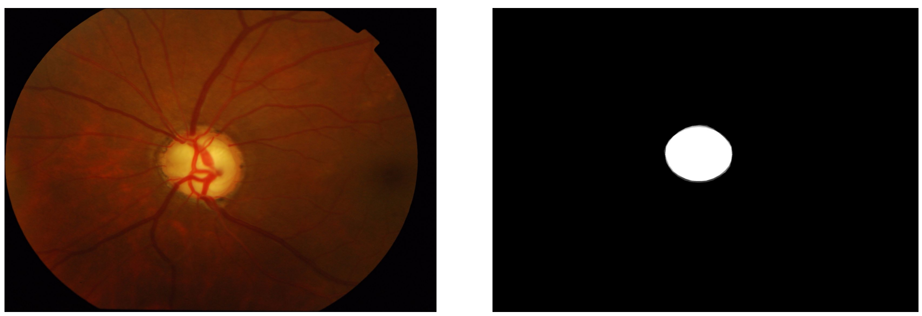


Figure 2.15: Example fundus image and a segmentation map from the DRISHTI Gs dataset

- **DRIONS DB:** The datasets consist of 2 folders: The image folder and Annotation folder by an expert ophthalmologist. The image folder contains 111 digital fundus images of both healthy and glaucoma categories. The annotation folders contain 111 segmentation maps for respective fundus images in the image folders where the segmentation maps are manually annotated by the various experienced ophthalmologists. Below **Figure 16** shows an example of a fundus image and a segmentation map from the DRIONS dataset.

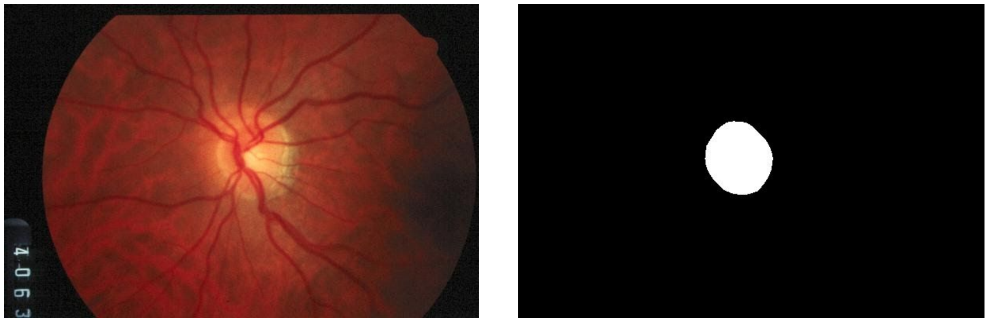


Figure 2.16 Example fundus image and a segmentation map from the DRIONS dataset

2. Evaluation metrics:

I have used the two most frequently used evaluation metrics to evaluate my model. They are:

- **Intersection over Union (IOU):** IOU is a simple but efficient metric to calculate how accurate the predicted mask with the ground truth mask. The calculation to compute the area of overlap (between the predicted and the ground truth) and divide by the area of the union (of predicted and the ground truth).

  The IOU metrics range from 0 to 1 where 0 signifies no overlap whereas 1 signifies perfect overlap between the predicted and ground truth mask.

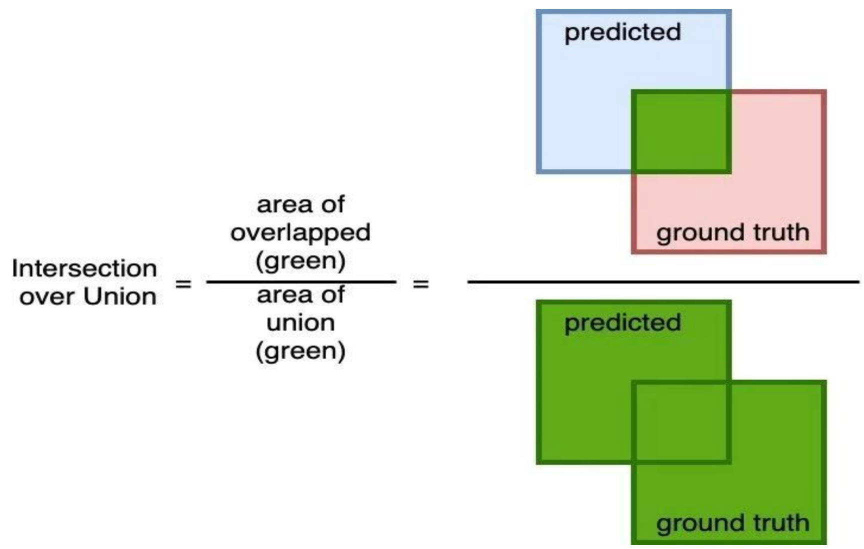


Figure 2.17: Intersection over union Evaluation metric

- **Dice Coefficient (F1 Score):** A common metric to measure the overlap between the predicted and ground truth mask. And it's calculated as 2 * the area of overlap (between the predicted and ground truth mask) divided by the total area (of both predicted and ground truth).

  Similar to the IOU metric this metric also ranges from 0 to 1 where 0 signifies no overlap and 1 signifies complete overlap between the predicted and ground truth mask.

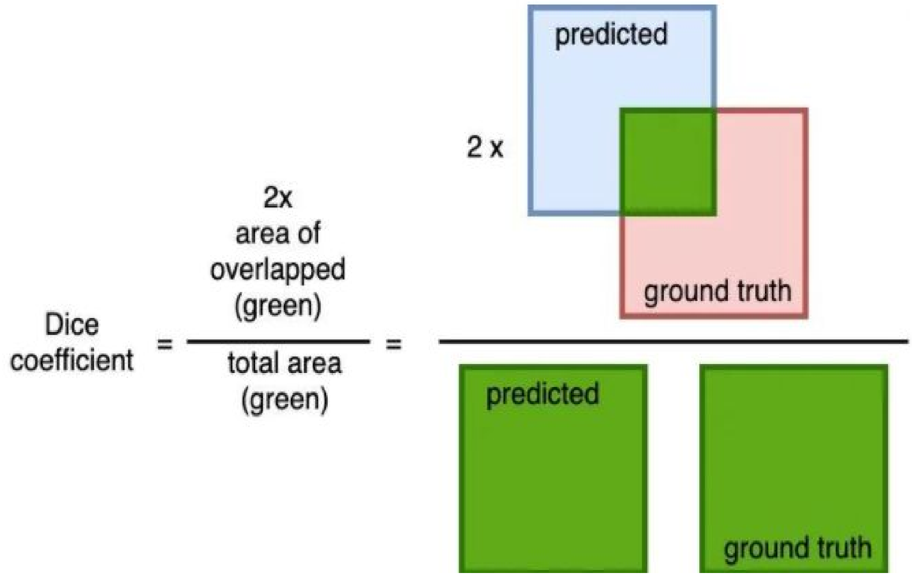


Figure 2.18: Dice Coefficient Evaluation metric

3. Comparison Results:

Let's look at how well my proposed Architecture performed compared to the U-Net Architecture and Residual U-Net Architecture based on the above evaluation metrics. Below **Table 1** shows the comparison of results for the optic disc segmentation task.

	RIM-ONE v3		DRIONS DB		DRISHTI GS	
	IOU	DICE	IOU	DICE	IOU	DICE
U-Net Architecture	0.8794	0.9142	0.8743	0.9158	0.8796	0.9128
Residual U-Net Architecture	0.8915	0.9287	0.8943	0.9312	0.8992	0.9396
Proposed Architecture	0.9176	0.9568	0.9245	0.9574	0.9134	0.9589

Table 3.1: Result comparison for the optic disc segmentation task

From the above table, we can see that there is an improvement in the result when comparing my proposed method with the U-Net Architecture this improvement due to the CLAHE preprocessing step as well as the residual blocks. Same way my proposed Architecture also performs better than the Residual U-Net Architecture due to the deeper Architecture and increase in filters to learn even more patterns from the fundus image. Now let’s see the result comparison of U-Net Architecture, Residual U-Net Architecture, and My proposed Architecture for optic cup segmentation task. Below **Table 2** shows the comparison of results for the optic cup segmentation task.

	RIM-ONE v3		DRIONS DB		DRISHTI GS	
	IOU	DICE	IOU	DICE	IOU	DICE
U-Net Architecture	**0.7215**	**0.8375**	**0.7301**	**0.8459**	**0.7289**	**0.8469**
Residual U-Net Architecture	**0.7689**	**0.8567**	**0.7721**	**0.8534**	**0.7718**	**0.8579**
Proposed Architecture	**0.8023**	**0.8902**	**0.8075**	**0.8973**	**0.8102**	**0.8954**

Table 3.2: Result comparison for the optic cup segmentation task

From the above table, we can confirm that the proposed method was better in segmentation of the optic cup compared to the U-Net Architecture. This improvement is due to the cropping along the area of the optic disc and deeper residual U-net architecture. In the case of comparing it with the Residual U-Net Architecture it's clear that my proposed precise enough because of the CLAHE and cropping along optic disc preprocessing steps. Now let's see the visual comparison of these models in below **Table 3**.

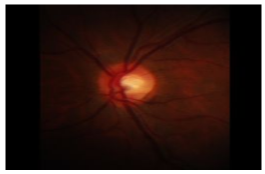
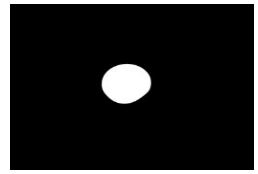
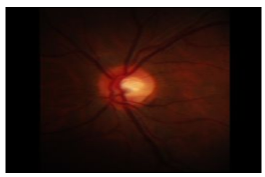
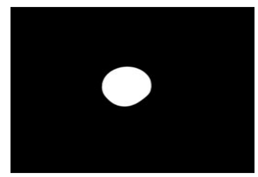
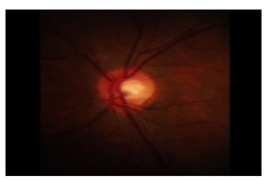
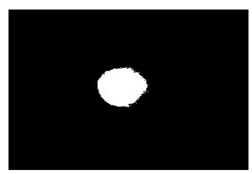
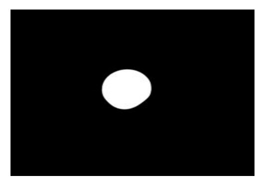
	Input image	Predicted Segmentation map	Correct Segmentation map
U-Net Architecture			
Residual U-Net Architecture			
Proposed Architecture			

Table 3.3: Visual Comparison of the results for the optic disc segmentation task

From the above table, it is clear that the proposed method produces accurate segmentation results compared to other models. The U-Net Architecture was able to extract optic disc without the noise but the results produced were not accurate enough to calculate the CDR (Cup-to-disc ratio) Whereas in the cases of Residual U-Net Architecture it also segments the noise along with the ROI (Optic cup and Optic Disc). My Proposed method overcomes both of these issues by using the CLAHE Module and deeper residual U-Net Architecture along with the increase in the no of filters. Let's take a look at the Visual Comparison for the optic cup segmentation task in below **Table 4.**

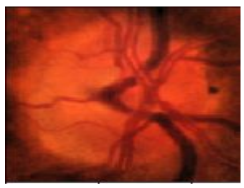
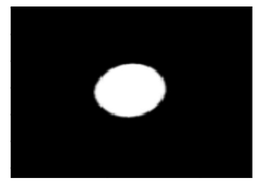
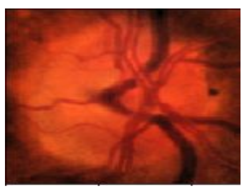
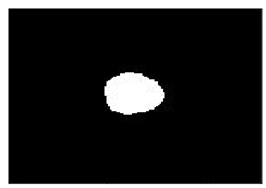
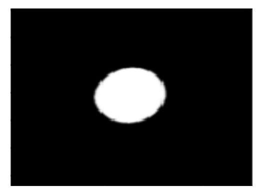
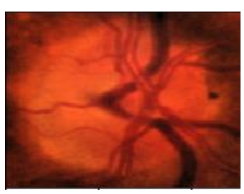
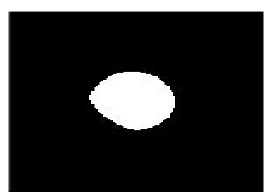
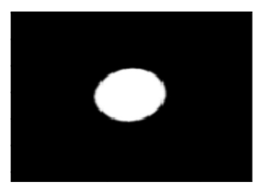
	Input Image	**Predicted Segmentation map**	**Correct Segmentation map**
U-Net Architecture			
Residual U-Net Architecture			
Proposed Architecture			

Table 3.4: Visual comparison of the results for the optic cup segmentation task

From the above table, we can see that the U-Net Architecture was not good at the segmentation of an optic cup from the input fundus image because of the noise on the optic cup region and also less focus over the optic cup region due to the small region. In the case of Residual U-Net Architecture, it was able to segment the ROI from the input fundus image but with the noise in it. In the case of my proposed method, it can efficiently eliminate noise as well as produce accurate results compared to the other two methods.

Chapter 5

Conclusion and Future Works

1. Conclusion:

In the section, we will see the overview of how my proposed method is cost-efficient and easily accessible to the small clinics and the hospitals. My proposed method is trained and tested on publicly available datasets like RIM-ONE V3, DRISHTI GS, and DRIONS DB which can be downloaded online. This way my model can be used even in small clinics and hospitals. And the proposed method mainly focuses on addressing the issue of extracting the optic cup and disc from the fundus image precisely compared to other methods. This helps the doctors in confirming the presence of glaucoma without the need for additional tests.

2. Future Works:

The Proposed method not only addresses the issue of extracting the optic cup and disc precisely from the fundus image. It also provides a path for detecting levels or stages of glaucoma in the patient. The stages of glaucoma mean the level of progression of glaucoma in every patient's eye which can help the doctors treat the patient accordingly and also avoid unnecessary tests to detect the glaucoma progression. This way it is economically friendly for patients and time-efficient for the doctors since no of people with glaucoma is large.

Chapter 6

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