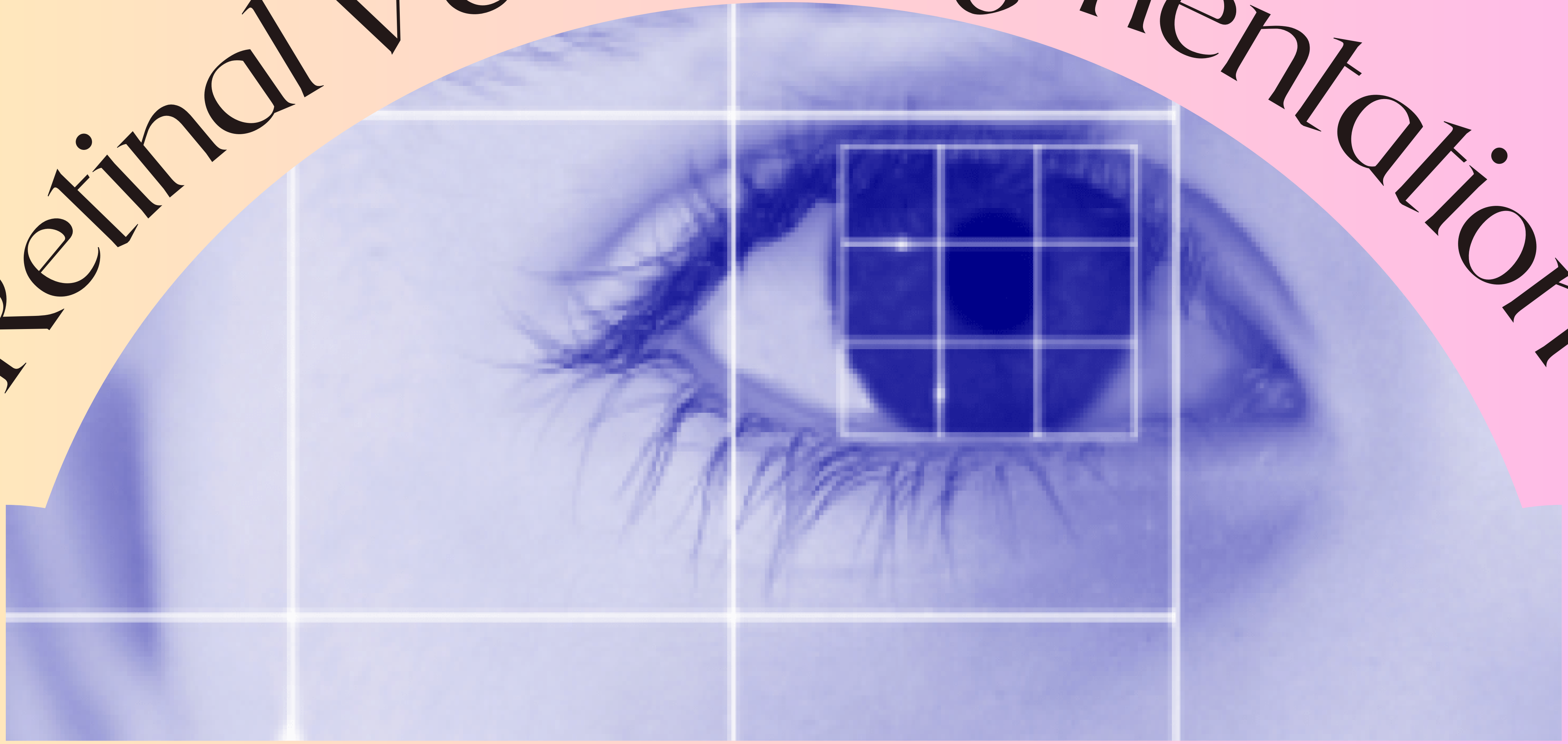
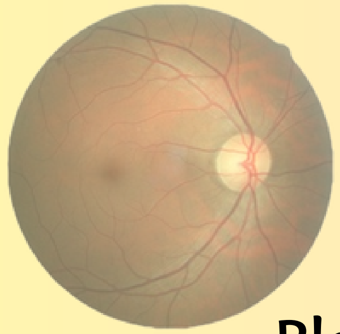
Retinal Vessel Segmentation



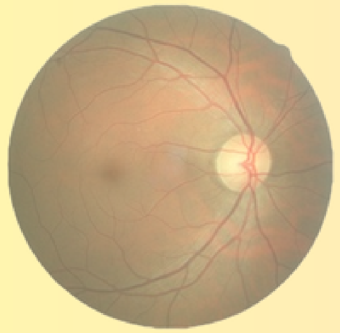
Tracing Retinal Vessels for Deeper Insights

Md Abuzar | Harbour.space University | 2023



Abstract

Blood vessels are important for keeping our bodies healthy, and doctors use their shapes to diagnose diseases and plan surgeries. In clinical practice, doctors diagnose diseases like diabetic retinopathy, macular edema, and arteriosclerosis using the morphology of vessels and perform surgical planning and navigation depending on the structure and location of vessels. For instance, geometric characteristics of retinal vessels, such as the vessel diameter, branch angle, and branch length, can be utilized for early diagnosis and effective monitoring of retinal pathology. The initial images of vessels from medical equipment aren't always clear, so specialists manually outline the vessels, which takes time. This is where automated vessel segmentation comes in – using technology to automatically outline vessels. Early methods used math and filters, but now, with deep learning (a type of advanced technology), computers can learn to do this task better than before, especially since the introduction of a significant model called U-Net. We are going to perform experiments with U-net and analyze the result.



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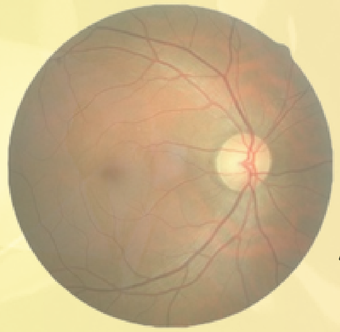
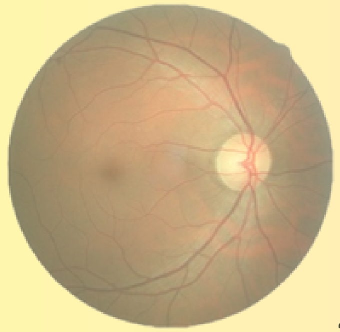


Introduction

Analysis of retinal vessel networks provides rich information about the conditions of the eyes. The morphological attributes of retinal vessels, such as length, width, tortuosity, and branching pattern and angles, play an important role in diagnosis, screening, and treatment. Segmenting blood vessels from fundoscopic images, which helps doctors diagnose better, is a tough task. The vessel edges are really thin and tricky to separate, plus the image quality might not be great. Images can have noise and important details could be hard to find for detecting diseases. A mistake here can lead to wrong diagnoses – saying someone has a disease when they don't or missing one when they actually do. Importantly, the image quality can be affected by lots of things like lighting, camera issues, wrong angles, and the kind of filter used.

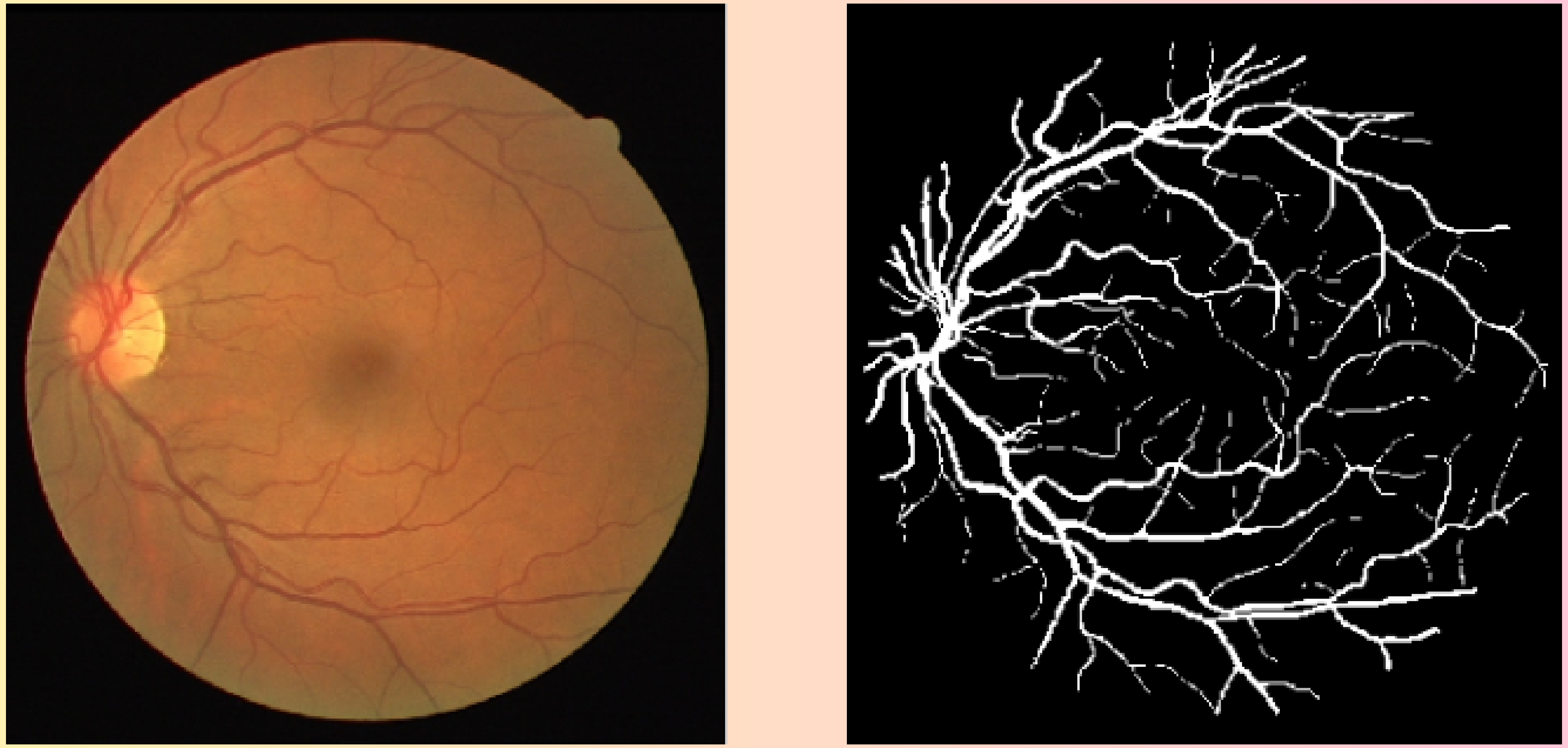
Medical Image Segmentation studies rely heavily on the U-Net architecture. we are using the DRIVE dataset, where each image in the training set addresses a different disease. The main challenge with the dataset is, we have little amount of data, and data is not annotated. So, We will be using the below approaches to set the experiments and analyze the result.

- U-Net Architecture with Data Augmentation.

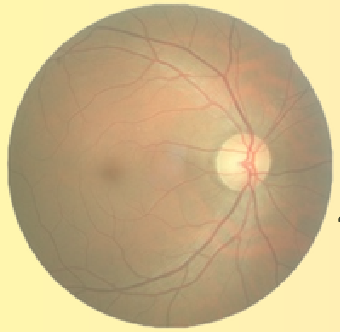


DataSet

In Retinal Vessel Segmentation problem, We will be using the DRIVE dataset. DRIVE dataset has 20 train and 20 test images. Each image in the training set addresses a different kind of disease. It is quite challenging to create a high-performance model with this amount of annotated data. The problem we are focusing on is the segmentation of retinal images with input data that has quality problems. Moreover, the amount of the annotated data is very limited.

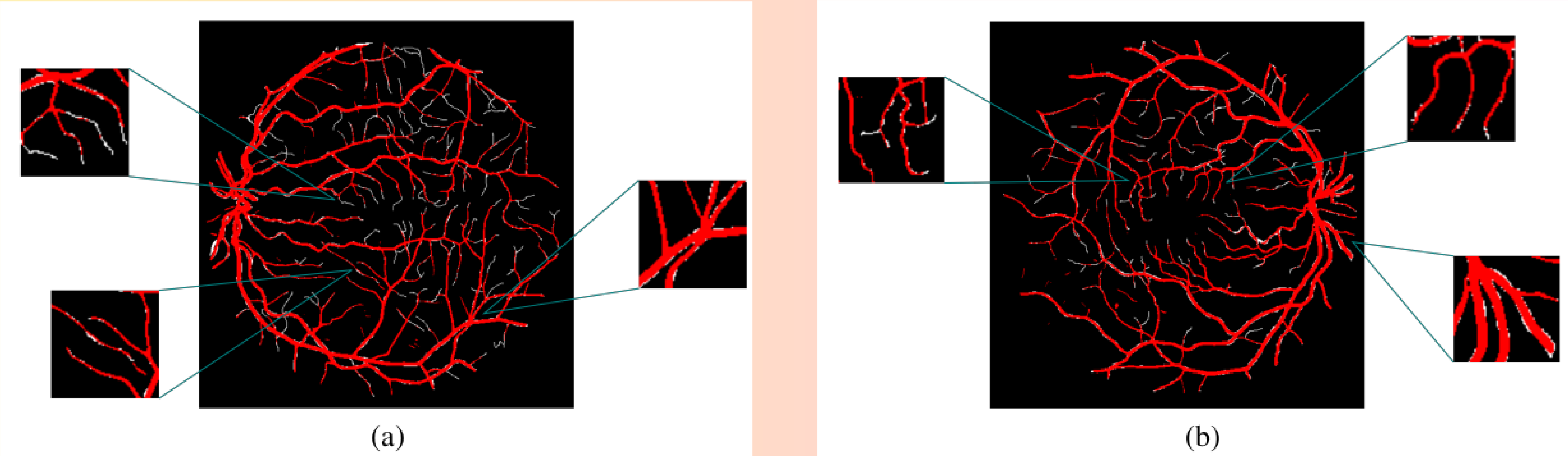


Training sample from DRIVE dataset

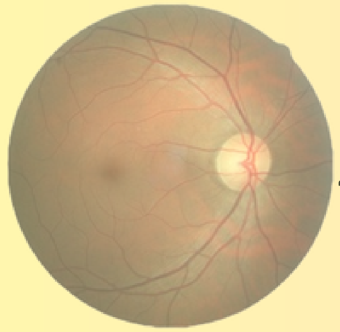


Problem with DataSet

The actual problem with the dataset is the segmentation of the minor vessels. Minor vessels are one of the hardest regions to segment. The below Figure shows the predicted and ground truth vessels together. It can be seen that the majority of the incorrect segmentations occur at the minor vessels.



Two examples for a combination of predictions and ground truths. Red pixels are predicted vessels, white pixels are ground truth pixels. By (a), it is observed that the model errors due to the minor vessels. The model performs well in segmenting thick vessels as it is pointed in the right hand side of (a). The model performs better at segmenting the vessels in (b). Minor vessels are segmented better than (a) in this example.



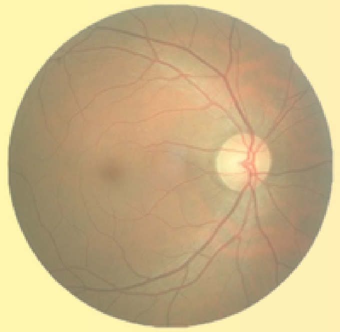
Literature Review

The convolutional networks have already existed for a long time, their success is limited due to the size of the available training sets and the size of the considered networks. The typical use of convolutional networks is on classification tasks, where the output to an image is a single class label. However, in many visual tasks, especially in biomedical image processing, the desired output should include localization, i.e., a class label is supposed to be assigned to each pixel. There is a general perception that successful training of deep networks requires many thousand annotated training samples. Thousands of training images are usually beyond reach in biomedical tasks.

The paper[1] presents a network and training strategy that relies on the strong use of data augmentation to use the available annotated samples more efficiently.

The paper[2] presents different kinds of Augmentation. Some of them are listed below:

1. Gamma Correction/Random Crop/Grid and Optical Distortion
2. White Noise/Elastic Deformations/Shift
3. Blurring/Dropout/Eq. Histogram
4. Rotation And Flipping



Experiment

Introduction

In this Experiment, We propose that optimal data augmentation can be successful for Retinal Vessel Segmentation, using simple U-Net architecture[3].

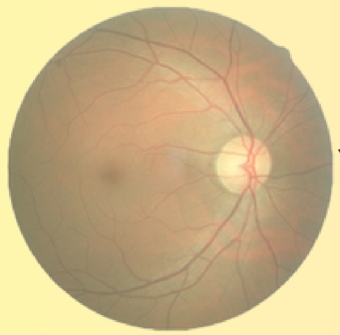
Data augmentation techniques are helpful for three reasons:

1. It is helpful because the input data is very scarce. Data augmentation techniques increase the input image size and provide the model with some extra information to learn.
2. Through data augmentation, we can recover some performance loss that occurred in the models due to the image quality.
3. Data augmentation will help with the segmentation model we used, which is the U-Net architecture that makes use of pooling operations. The model learns relatively lower from the corner and side parts of the input image.

We use data augmentation techniques that rely on adding noise to the original image so that our model can learn more from the noisy images. Noise data come from the normal distribution with mean 0 and standard deviation. In our study we use augmentations with different epsilon values each greater than or equal to 1.

An attempt to increase the success of the segmentation model we might add zoomed images to the dataset. Randomly cropping the input image with the random sizes might be another strategy. We use shifting and flipping of the input image which are also two successful data augmentation techniques. They are widely used with U-Net model training because U-Net uses convolutional filters. Convolutional filters miss the information in the edge of images. Shifting technique pushes the edges of images to the more central part of the image so that the U-Net model can learn the information in the edges of the original image from this augmented image.

Architecture



What is U-Net?

U-Net is a special type of computer model designed to understand and process images. It's called "U-Net" because its shape looks a bit like the letter U. It's really good at tasks like segmenting, which means drawing lines around important parts of an image.

How Does U-Net Work?

Think of U-Net as having two main parts: the left side (the top of the U) and the right side (the bottom of the U).

1. Contracting Path (Left Side): The left side helps U-Net understand the big picture. It takes the input image and breaks it down into smaller details using layers called "convolutional layers." This part helps U-Net learn different features, like edges and textures.
2. Bottleneck (Middle): This is like the center of the U. It combines all the details learned from the left side and tries to make sense of them. It understands what's important and what's not.
3. Expanding Path (Right Side): The right side of the U is where U-Net puts everything back together. It uses "deconvolutional layers" to create a new image. But this new image has important parts outlined. It's like putting the missing puzzle piece back in place!

Why is U-Net Useful?

U-Net is super helpful in medical imaging, like finding blood vessels or tumors in scans. It can learn from a lot of examples and get really good at spotting these things. With U-Net, doctors can save time and make better decisions about treatment.

In simple words, U-Net is like a smart artist that can draw lines around important things in pictures, making it easier for doctors to see what's going on inside the body.

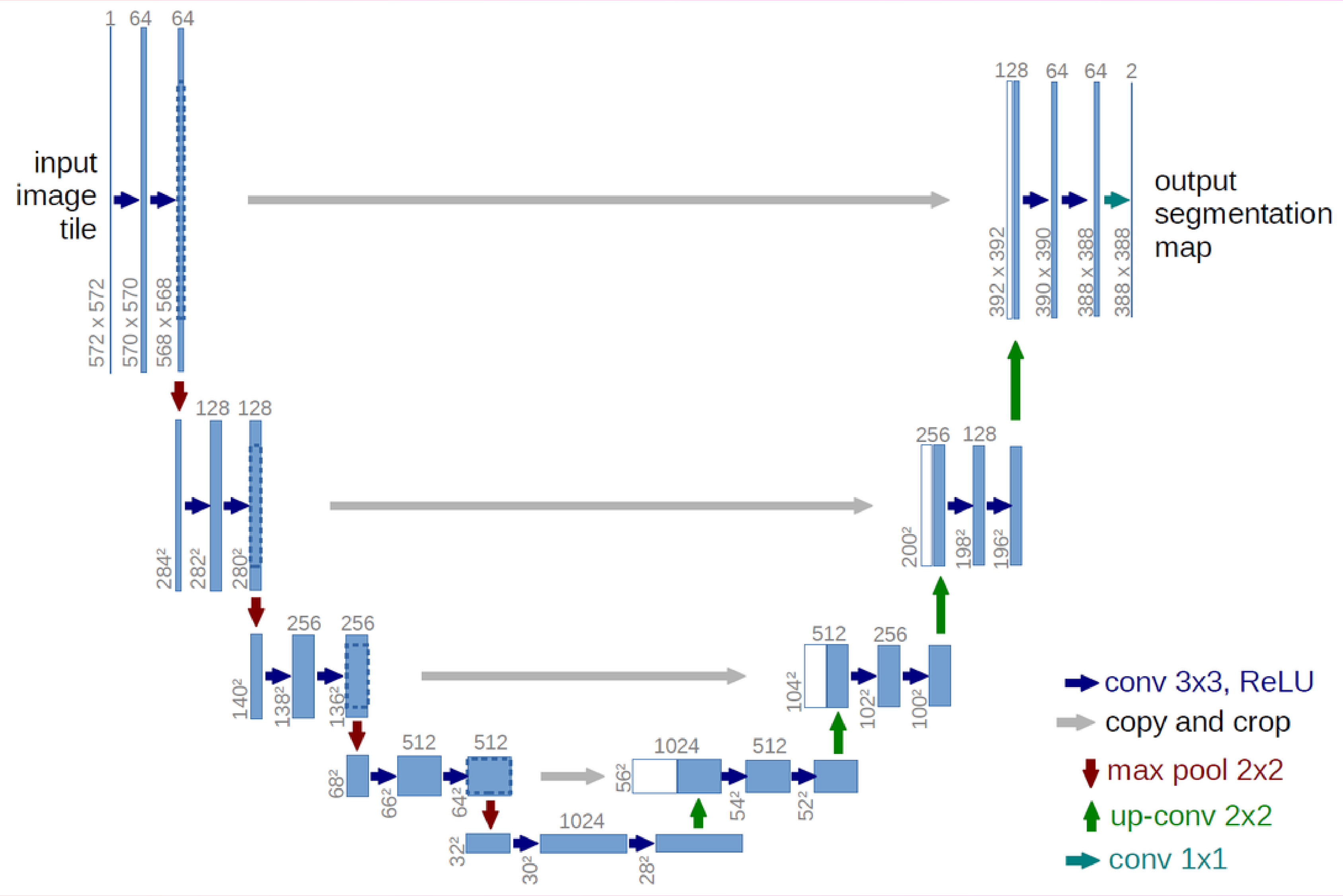
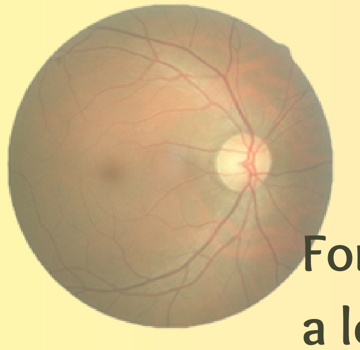
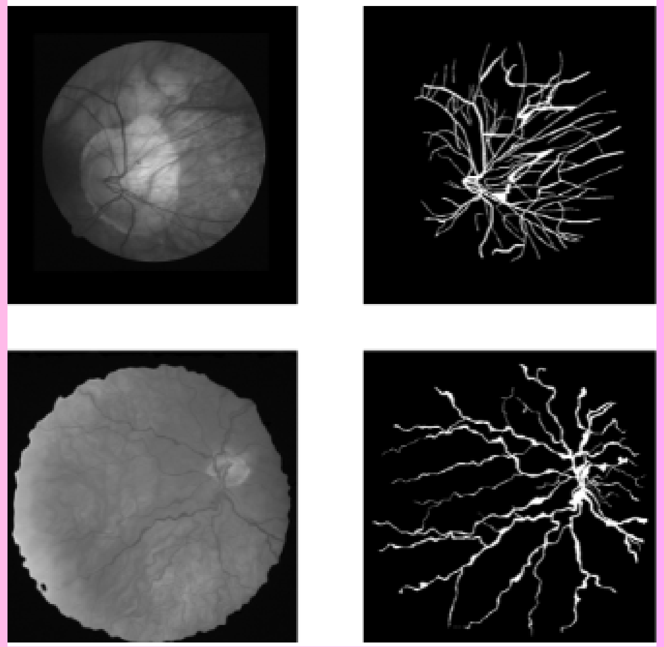


Figure 1: Architecture of the U-Net Image Segmentation Model.



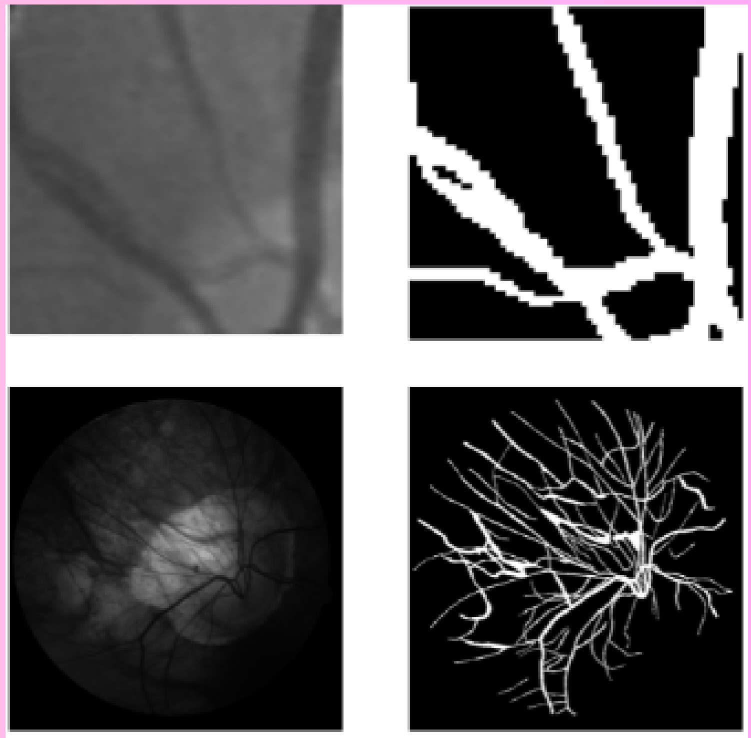
Experiment set up



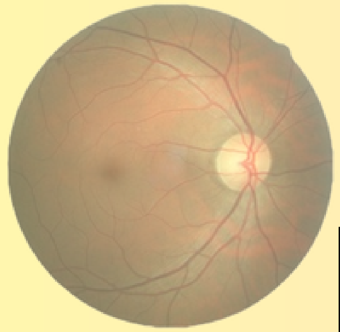
For our method, we use the architecture from U-Net [3]. We train our models with the Adam optimizer [4] with a learning rate of 1e-4, **β** 1 = 0.9, **β** 2 = 0.999. We don’t use any learning rate scheduling algorithms.
For experiments on DRIVE, we use mini-batches of size 3. We use a dropout probability of 0.1 on the fourth and fifth convolutional layers. The training is done by using binary cross-entropy loss. In our study, we experimented with dice loss and the combination of binary cross-entropy loss and dice loss [5] as well.
Nevertheless, it is observed that the best results are obtained using binary cross-entropy loss.
We have generated 70 images from 20 images by using augmentation in this experiment.

we used the below augmentation:

1. Rotation (30*k) And Flipping
2. Zoom Out
3. White Noise/Elastic Deformations/Shift
4. Gamma Correction/Random Crop/Grid and Optical Distortion
5. Blurring/Dropout/Eq. Histogram



We used albumentations, imagecorruptions libraries for excessive augmentations.



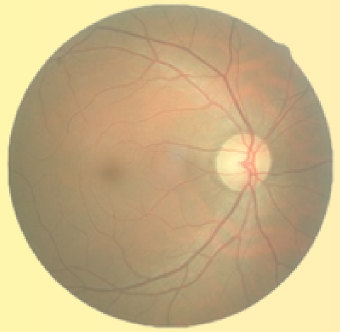
Results

DRIVE	Accuracy	AUC	Mean Dice Coef
Rotation (30*k) And Flipping	0,970	0,971	0,809
+ Zoom Out	0,971	0,983	0,820
+ White Noise/Elastic Deformations/Shift	0,970	0,985	0,822
+ Gamma Correction/Random Crop/Grid and Optical Distortion	0,971	0,983	0,824
+ Blurring/Dropout/Eq. Histogram	0,971	0,985	0,826

Result calculated for different kind of augmentation

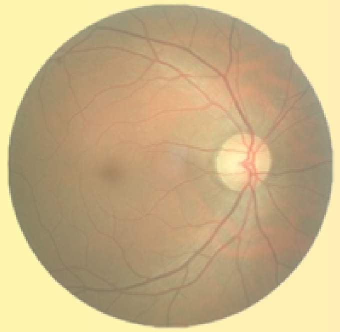
Method	AUC	Accuracy
UNet (2018*)	0,9752	0,9555
Residual UNet (2018)	0,9779	0,9553
IterNet (2019)	0,9816	0,9571
SUD-GAN (2020)	0,9786	0,9560
RV-GAN (2020)	0,9887	0,9790
U-Net with Augmentation	0,9848	0,9712

Performance comparison for different Methods



Code Repository

- https://github.com/abuzarmd-ML/Image-Segmentation-DRIVE-dataset



References

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[2] https://arxiv.org/pdf/2007.15883v2.pdf

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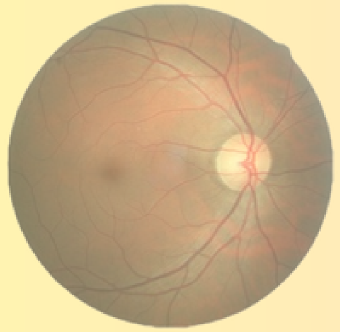

THANK YOU