

# Exploring the Performance of a Modified U-Net & Dense-Net Combined Model for Retinal Blood Vessel Segmentation using the Drive Dataset.

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## Abstract

As medical imaging plays vital role in the diagnosis and treatment of ailments, the realm of medical image processing has gained significant appeal among researchers. The accurate retinal blood vessel segmentation in fundus is of great practical significance to help diagnosis retinal diseases. This paper aims to solve the problems of serious segmentation errors and low accuracy in traditional retinal segmentation. We are initiating to propose a modified combination of U-Net and Dense-Net architecture. This will improve deep network performance and speed up the learning process. We used to pre-process techniques, including adaptive histogram equalization for contrast enhancement and median filtering for noise reduction. It improves overall quality of input image data. Random retina image blocks are used as training data to make it robust and generalized. The Dense-U-Net model has showed more accuracy in retinal segmentation than other traditional algorithms.

**Keywords:** *U-Net, Dense-Net, Retinal Blood Vessel, Retinal Segmentation*

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## 1. INTRODUCTION

**Problem Statement:** Medical image segmentation is the process of assigning specific class labels to individual pixels of assigning specific class labels to individual pixels is an image with the goal of precisely defining anatomical structures. Since it empowers on different organs and tissues, like liver, heart, blood vessels etc. Glaucoma is a condition in which the pressure inside the eye rises, causing damage to the optic nerves and eventually causing vision loss. Treatment at an early stage is essential to avoiding permanent blindness. However, the early symptoms of glaucoma are often missed by many patients. It is an eye disease that vandalizes the optic nerve and Retinal Nerve Fiber Layer. At present, glaucoma affects approximately 80 million people around the world. People having age greater than 55 years at a higher risk. Glaucoma is the second leading cause of blindness in the world while cataracts is in first position. The retinal slim organization, which assumes a significant part in eye wellbeing, should be visible utilizing painless procedures like ophthalmoscopy, etc. With this retinography, it can catch computerized pictures of the retina, making excellent records of the retinal vessel's appearance. Though, it takes time

for specialists to manually trace the blood vessels in these images. As a result, computer programmers are looking into automated approaches to analyzing those images. These approaches have the potential to provide accurate measurements.

**Hypothesis:** Integrating the U-Net and Dense-Net architectures will significantly improve the accuracy and robustness of retinal blood vessel segmentation compared to using either traditional architectures or other state-of-the-art models. Dense-Net's segmentation is more accurate than the other segmentation models and its adaptive histogram equalization will enhance the input image data, therefore it will lead to more accurate and reliable segmentation results.

**Research Question:** Thus, the proposed study reports on 2 interrelated research questions

1.Does combining the U-Net and Dense-Net improve accuracy of retinal blood vessel segmentation?

2.Does combining the U-Net and Dense-Net have impact the Area Under ROC Curve (AUC)?

## II. RELATED WORKS

Previously different researchers proposed different types of U-Net model for Retinal Blood Vessel Segmentation. Some of these are written below-

Rutuja [1] in her work, using LeNet architecture consists of two sets of convolutional layers, activation layer and pooling layers, which is followed by a fully connected layer and finally a SoftMax classifier. Image dimension used for the purpose of that model are 256\*256. That model was trained in 25 epochs with a learning rate of 0.0001. 99% accuracy was achieved by using LeNet. Advantages of using that model: (i) LeNet can be trained in very less time, (ii) LeNet does not need any GPUs for its training. Limitations of using that model: (i) It was not designed to work on large images.

Manuel et al. [2] in their work, applying a fully Convolutional Neural Network (CNN) directly on the original color retinal image to segment the vascular structure. In this network not taking full fundus image it takes as input 256\*256 pixels sub-images for work. 98% accuracy was achieved by using this model. Advantages of using that model: (i) It can be efficient for image processing, (ii) It can give high accuracy. Limitations of using that model: (i) It needs high computational requirements, (ii) It occurs difficulty with small datasets.

Ali et al. [3] in their work, applying the idea of U-Net, where extracted features at different levels in the encoding path are combined with the feature maps in the decoding path. In this model dataset contains both training and testing set where every set includes 20 RGB retinal images with the pixel size of 565\*584. With that model

98% accuracy were achieved. Advantages of using that model: (i) it has the ability to handle high-resolution images to produce accurate segmentation maps, (ii) It is better than CNN. Limitations of using that model: (i) It's skip connections impose an unnecessary restrictive fusion scheme.

Almustofa et al. [4] in their work, they proposed an algorithm that has two steps called optical disc and optical cup segmentation on retinal image based on multimap localization. Two datasets were using in this model one is Drishti-GS with 2047\*1760 resolution and another one is Refuge dataset with 2124\*2056 resolution. With Drishti-Gs dataset 95% accuracy were achieved and with Refuge dataset 87% accuracy were achieved. The advantages of using that model: (i) It plays a vital role for diagnosing glaucoma. Limitations of using that mode: (i) Rising eye pressure can damage optic nerve.

Olaf et al. [5] in their work, fully convolutional network. Only a set of 30 images use to train data with the pixel size of 512\*512. In this model 92% of accuracy achieved. Advantages of using this model: (i) It can train small number of image dataset, (ii) Avoiding the use of dense layer so that we can make the network learn faster. Limitations of this model: (i) It is a slow and complicated if we want a good pre-trained model. (ii) It cannot accurately represent how a signal is processed by a nonlinear system.

Haung et al. [6] in their work, in this paper densely connected convolutional networks used. In the paper they use Resnet, Composite function, Pooling layers, bottleneck layers. Two CIFAR datasets were used in this with 32\*32 pixels images. Advantages of using this model: (i) Strong gradient flow, (ii) Computational efficiency. Limitations of using this model: (i) Data is replicated multiple times.

**Objective of the Research:** According to the research questions, objective of this paper is

- 1.To examine the performance of U-Net and Dense-Net combination for improvement accuracy on retinal blood vessel segmentation.
- 2.To evaluate AUC of the combined proposed model.

## **2. LITERATURE REVIEW**

This paper presents a novel approach to retinal blood vessel segmentation using U-Net and Dense-Net architectures, aiming to improve deep network performance and expedite the learning process. Traditional methods like adaptive histogram equalization and median filtering are used as preprocessing techniques, while random retina image blocks are used as training data. The hybrid architecture enhances feature reuse, gradient flow, and information propagation, leading to more accurate segmentation results. The model's success is evaluated using the DRIVE dataset.

### 3. PROPOSED METHOD

In this report, we initiated to propose a modified method based on U-Net architecture which has significant performance in image segmentation. We used U-Net for Retinal Blood Vessel segmentation. However, to overcome the challenges of low segmentation accuracy and incomplete segmentation of small vessels, this paper will suggest a modified approach that combines U-Net and Dense-Net models. The suggested technique integrates the application of Adaptable Histogram Equalization along with limitation of contrast which is known as CLAHE. It enhances the contrast and visibility of image details. We also intend to test and apply data normalization techniques such as median filtering, to reduce noise and enhance the overall quality of the input data. It will make the input dataset more robust to train and test. Integrating Dense-Net, known for its dense connectivity pattern, into the U-Net framework will give us both models' benefits. We will be able to enhance feature reuse, gradient flow, information propagation, resulting in improved representation.

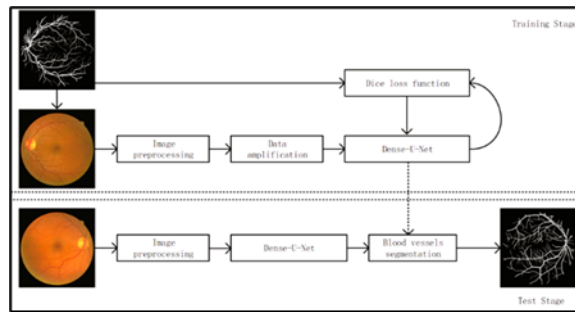


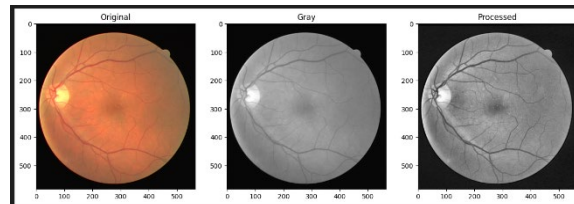
Figure 01: Proposed Model Flowchart

Our goal is to improve segmentation accuracy and address the challenges associated with segmenting complex structures, including small and complicated details. We are intending to base our approach according to the mentioned flowchart (Figure 01).

### 4. RESULTS

In this section, the experiment carried out based on the proposed method is explained using Driver Dataset. We have collected this dataset from [Kaggle site](https://www.kaggle.com/datasets/ahmedmohamed97/driver-dataset).

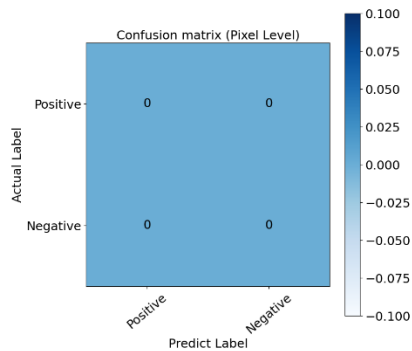
We have pre-processed the input image data from the Driver dataset we collected. After that, we plotted the retinal image into three categories



After pre-processing, we compared between two method A and B side by side. By displaying the images side by side, it allows for a direct visual comparison of the

outcomes produced by the two methods.

When pre-processing is done, we trained the dataset with processed input images. There we processed and generated image/mask patch. To train our model, we initialized the epoch to 5 and batch size to 25. Then the model started to train and generate validation data. We finished this segment by loading and compiling the model and after that we train the model.



The confusion matrix is  $\begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$ .

In terms of evaluating the performance of a model, a confusion matrix where all values are zero (such as  $\begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$ ) typically indicates that there is no information to assess the model's performance. This means that the model did not make any predictions, and therefore, it is not possible to evaluate its accuracy, precision, recall, or other performance metrics.

## 5. DISCUSSION

The proposed segmentation model can perform medical image segmentation tasks using U-Net, requiring fewer resources. It achieves the highest dice score of over 90% for each dataset. Reducing parameter number leads to nominal performance degradation and a drop in dice score, requiring a significant reduction in model size.

## 6. CONCLUSION

We initiated to propose a modified model of the combination of u-net and dense-net to improve retinal segmentation. We pre-processed, train and tested our dataset. Although the confusion matrix showed  $\begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$ , that means it didn't predict any result from the input image data.

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## 8. CONTRIBUTION

	Tanjil Hasan 1	Emon Singha 2	Saadman 3	Fayzur 4	Contribution (%)
	20-43633-2	20-42344-1	19-41562-3	20-43330-1	
Conceptualization	50%	40%	5%	5%	100 %
Data curation	30%	30%	20%	20%	100 %
Formal analysis	30%	30%	20%	20%	100 %
Investigation	50%	40%	5%	5%	100 %
Methodology	50%	30%	20%	0%	100 %
Implementation	30%	40%	20%	10%	100 %
Validation	50%	30%	10%	10%	100 %
Theoretical derivations	25%	25%	40%	10%	100 %
Preparation of figures	50%	50%	0%	0%	100 %
Writing – original draft	40%	40%	10%	10%	100 %
Writing – review & editing	40%	50%	5%	5%	100 %