A Hybrid CLAHE-GAMMA Adjustment and Densely Connected U-NET for Retinal Blood Vessel Segmentation using Augmentation Data

Erwin, *Member*, *IAENG*, Hadrians Kesuma Putra, Bambang Suprihatin, Fitri Ramadhini

***Abstract*— The retina is a thin layer on the back of the eyeball that is sensitive to light. Retinal blood vessels function to supply blood and oxygen to the retinal tissue. If there is a disturbance in these blood vessels, we need to detect a disease or other disorder in the retina. One of the stages in image recognition is segmentation. This study used the Convolutional Neural Network method with U-Net architecture for retinal image segmentation. Before the segmentation stage, preprocessing processes such as grayscale conversion, standardization, Contrast Limited Adaptive Histogram Equalization (CLAHE), and gamma adjustment are carried out. Furthermore, the retinal image that has been improved in quality will be segmented. This segmentation separates the background and foreground to obtain retinal blood vessels. The last stage measures the performance of the segmentation results using the parameters, namely accuracy, specificity, sensitivity, F1 score, and Jaccard similarity score. The dataset used in this study is the DRIVE. Data augmentation is done to increase the amount of data. It tested the results using the activation function Sigmoid and rectified linear unit (ReLU) with different kernel sizes, namely 3 x 3, 5 x 5, and 7 x 7. The best research results with this method get an accuracy of 95.48%, sensitivity 74.91%, specificity 98.48%, F1 score 80.84%, and Jaccard similarity score 67.84% using ReLU activation function with kernel size 5 x 5. The method used is better and more efficient for image segmentation.**

***Index Terms*—Blood Vessel, Convolutional Neural Network, Retinal, Segmentation, U-Net**

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I. Introduction

Technology and information continue to develop very rapidly until recently. Data and information that we can receive or get are in text and the form of images, audio, and video. Compared to text, images are better able to provide us with a lot of information because images are a multimedia component in visual information. By utilizing existing technology, we can process images or what is commonly known as Digital Image Processing.

The retina itself has several other objects such as the optical disk, blood vessels, exudate, etc. Early detection of retinal disease can be done through the passage of the blood vessels of the retina. Before carrying out the initial diagnosis process on retinal blood vessels, which will be used as an advanced stage for the medical personnel, it is necessary to improve and improve the quality of the retinal image with the final focus on taking the segmentation results from the retinal blood vessels. Segmentation is separating features that are used from features that are not used [1].

The neural network-based method that is currently popular is deep learning. The classification process is currently a widely used deep learning method that has grown rapidly used in various studies [2]. One of the popular methods is Convolutional Neural Network (CNN). CNN can handle large-dimensional data such as images because the input to CNN is in the form of a matrix [3]–[5]. One of the most widely used CNN architectures for segmentation in medical image analysis is U-Net [6]. U-Net is one of the architectures commonly used in medical analysis. In addition to having accuracy in terms of feature target segmentation, U-Net can increase the accuracy of diagnoses using medical images [3], [7]. U-Net architecture can provide better performance on medical images.

Several other approaches that use U-Net include Ronneberger et al. [6] applied U-Net for the segmentation of medical images. Soomro et al. [8] modified U-Net architecture with Variational Auto-Encoder (VAE) on eye blood vessel segmentation. Li et al. [9] combined Deformable-ConvNet and U-Net is also on eye blood vessels. Another study using U-Net is Yan et al. [10] on Digital Retinal Image for Vessel Extraction (DRIVE) and Structured Analysis of the Retina (STARE) datasets, Jin et al. [11] combined deformable and U-Net on the DRIVE dataset.

Unfortunately, these studies still produce a sensitivity below 77%. U-Net architecture has several layers deep enough [12]. Adding layers directly to the U-Net network can increase the parameters and complexity of the network. This can lead to vanishing gradient problems and excessive complexity during training [13], especially for large images.

Data augmentation is a common way to reduce over-fitting. Over-fitting is a condition that occurs when a model has a low error during training but performs poorly when predicting new data. Data augmentation will generate new data using the transformation of the original data. Data augmentation makes it possible to increase the generalizability of the data. This study carried out data augmentation with rotational transformations, namely horizontal, vertical, and reverse vertical flip.

The process of data augmentation can increase segmentation accuracy, which is more significant than segmentation without data augmentation. This can have an effect because the data augmentation process can increase the amount of training data based on the probability value of the retinal image. Increasing the amount of trained data can improve system performance in segmenting blood vessels in retinal images.

This study aimed to obtain the results of blood vessel segmentation in retinal images and measurement results such as accuracy, specificity, and sensitivity. One of the benefits expected from this research is to fulfill various advanced stages in the early diagnosis of retinal disease in the medical field.

The novelty in this research is a hybrid between image enhancement, namely Contrast Limited Adaptive Histogram Equalization (CLAHE) and gamma adjustment with segmentation using CNN, namely Densely Connected U-Net architecture. The most contributing results were an increase in the accuracy value of 1% and a specificity of 1.5% in the proposed method compared to the Single Convolutional Neural Network. The proposed technique also works well compared to other available strategies regarding accuracy, sensitivity, specificity, false positive rate, true positive rate, and the area under the receiver operating characteristic (ROC) curve.

II. Related Work

In [14] conducted an experiment, namely segmenting blood vessels in the retina using the mathematical morphology and K-means clustering approaches. Before doing the segmentation process of the blood vessels, [14] improved image quality using mathematical morphology. The enhanced image is then segmented using the K-means clustering algorithm. [14] conducted the research using the DRIVE dataset and obtained results with an approach, showing that this method is quite effective because it achieves an average accuracy of 95.10% and the best accuracy of 96.25%. However, the K-means clustering method has weaknesses. If there are many data points, for example, one million data, then the calculation and finding the nearest point will take a long time [14].

Furthermore, the Single Convolutional Neural Network method was researched [15]. On average, segmentation can correctly classify up to 92.68% of the fundamental truth in the test set from the Drive dataset. The highest accuracy achieved in a single image is 94.54%, and the lowest is 88.85%. The Single Convolutional Neural Network can be used for vascular segments and optical discs and fovea with good or good accuracy. Using a Convolutional Neural Network to segment blood vessels, optical disc, and fovea from a fundus image is not the same as number recognition, or image categorization in at least three aspects. As an example of the problem in this paper, segmentation is carried out by classifying the membership of each pixel. In contrast, most other issues only identify the membership of an image or a segment [15].

There is a method, namely the Hybrid CGLI Level Set Method, based on the Selective Binary and Gaussian Filtering Regularized Level Set (SBGFRLS) model and the Local Binary Fitting (LBF) model, which was studied by [16]. The results of the segmentation of this method can be well controlled and provide the ability to handle pathological images. This method also has the desired quantification results compared with other unsupervised retinal image segmentation results. The results obtained an average accuracy of 93% in the DRIVE dataset, a sensitivity of 73%, and a specificity of 96%. The STARE dataset obtained an average accuracy of 94%, a sensitivity of 74%, and a specificity of 96%. The proposed method can segment retinal image vessels to the desired extent, but the weaknesses of the SBGFRLS method and the LBF model cannot work well in direct or real-time segmentation [16].

Another method that can be used is the Modified Iterative Self Organizing Data Analysis Technique (MISODATA) based on global and local thresholding, researched by [17]. Previously, the retinal image contrast was enhanced using CLAHE, then using a Gaussian blur filter to remove noise. The research results with this method obtained an average accuracy of 95.2% and 95.7%, an average sensitivity of 78% and 74.5%, an average specificity of 97.2% and 97.4%, respectively. DRIVE and STARE datasets, respectively. Based on the results obtained, the accuracy, durability, low complexity, and high efficiency make this method an efficient method for analyzing retinal images. However, this methodology cannot recognize the retinal vessels from the background for thin retinal vessels and often loses some vascular connectivity [17].

III. Proposed Methodology

A. *Retinal Image Dataset*

The dataset to be used is the DRIVE (Digital Retinal Images for Vessel Extraction) dataset. The photographs for the DRIVE database were obtained from a diabetic retinopathy screening program in The Netherlands. The screening population consisted of 400 diabetic subjects between 25-90 years of age. Forty photographs have been randomly selected, of which 33 do not show any sign of diabetic retinopathy and seven show signs of mild early diabetic retinopathy.

The DRIVE database has been established to enable comparative studies on the segmentation of blood vessels in retinal images. The set of 40 images has been divided into 80% training and 20% data for testing.

B. *Method*

The preparation of system design and methods in this study will be made in the form of a flowchart so that the stages to be carried out are structured and follow the objectives to be achieved. The flowchart in this study is shown in Figure 1.

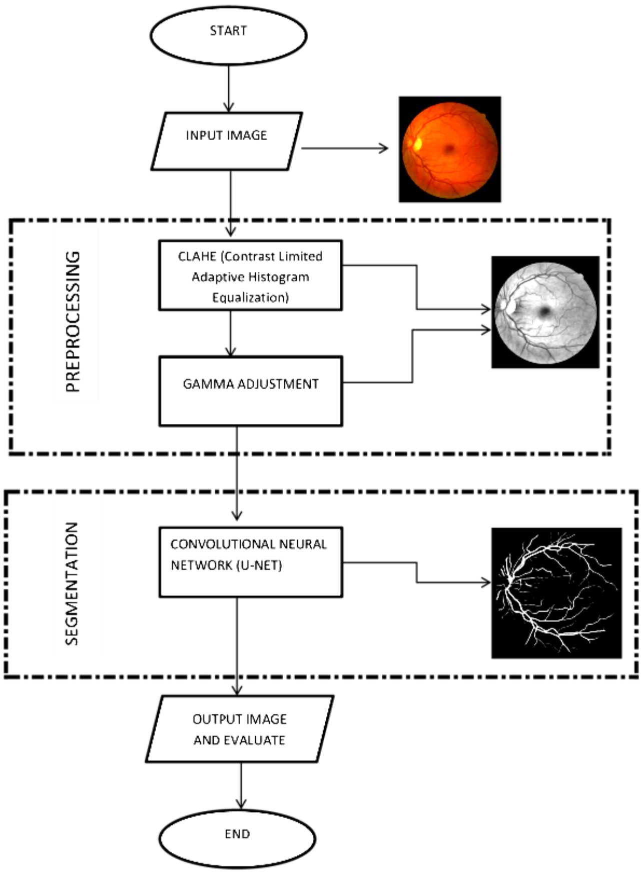


Fig. 1. The flow chart of the proposed method consists of the enhancement, segmentation, and evaluation processes

From the flowchart shown in Figure 1, it is known that the flowchart sequence, in this case, is divided into five stages. The first process is image input, then preprocessing includes CLAHE and gamma adjustment, the next process is segmentation, and then output images and the last is the evaluation results.

C. *Pre-processing*

1) *Grayscale conversion*

The original retina image of the DRIVE dataset is still in RGB (Red, Green, and Blue) format. Therefore, in this process, the original retinal image will be converted to grayscale or grayscale to facilitate image processing. Grayscale is a color pixel that has a gradient range between black and white, the intensity of the grayscale image is stored in 8 integer bits which give 256 possibilities, starting from level 0 to 255 (0 for black and 255 for white and the values between them are degrees of gray).

A grayscale image is an image whose only color is shades of gray. The reason for distinguishing such images from other color images is that less information needs to be provided for each pixel. Gray is a color in which the red, green, and blue components have the same intensity in the RGB space. It is necessary to define a single intensity value for each pixel instead of the three intensities required to define each pixel at all color images. Often, the grayscale intensity is stored as an 8-bit integer giving 256 possible shades of gray that vary from black to white [18].

2) *Dataset normalized*

The goal of data normalization is to change the numeric column values in the data set to the same scale without changing the range of values. For machine learning, each dataset does not require normalization. This is necessary only if the features have different ranges. Normalization is a good technique to use if you don't know the distribution of your data or if you know the distribution is not Gaussian (a bell curve). Normalization is useful when your data is of varying scale, and the algorithms you use do not make assumptions about the distribution of your data, such as k-nearest neighbors and artificial neural networks.

3) *Standardization*

Standardization of features around the center and 0 with a standard deviation of 1 is important when comparing measurements with different units. Variables measured on different scales do not contribute to the analysis and may result in bias. Standardization is useful when your data is of varying scales. The algorithms you use make assumptions about your data with a Gaussian distribution, such as linear regression, logistic regression, and linear discriminant analysis.

4) *Gamma adjustment*

Gamma adjustment is one of the simplest global tone reproduction operators shown in equation (1). If an image is too bright or too dark, the image can be made pleasing by applying a gamma greater than one (leading to a darker image) or less than one (leading to a brighter image) respectively [19].

$$V_{out} = V_{in}^{\gamma} \tag{1}$$

where V_{in} is input and V_{out} is output. The output image will look brighter if γ is greater than 1. And if γ is smaller than 1, the image will look darker.

5) *CLAHE*

CLAHE is used to improve retinal image quality [20]. CLAHE divides the entire image into minutes of identical size and works on each section where the contrast of the individual sections is increased. The histogram of the output image matches the histogram defined by the distribution parameters. The adjacent small sections are then held together using bilinear interpolation, removing artificially induced boundaries. Excessive noise amplification can be avoided by limiting the contrast of individual homogeneous sections [20].

It is difficult to differentiate between intensity variations of the vessel and non-vessel segments in retinal images. To enhance the algorithm result, intensity transformation is applied to increase the intensity gap between vessel and non-vessel pixels [17]. In this research, to enhance the color of retinal images, we use Contrast Limited Adaptive Histogram Equalization (CLAHE). An enhanced contrast can be expressed as the slope of the function connecting the input value of image intensity to the desired image intensity. Contrast can be limited by limiting the tilt of this related function. Also, the enhanced contrast is directly related to the height histogram at that intensity value [21].

CLAHE enhances local contrast by not greatly amplifying the noise present in a relatively homogeneous area and is used in many retinal vessel segmentation methods. Furthermore, noise is suppressed by opening the image morphologically using a circular structuring element with a radius of 8 pixels [22].

D. Segmentation

The next process after preprocessing is the segmentation process. Image segmentation is crucial for separating the background and important features in the image [23]. In this study, the authors used the Convolutional Neural Network method to obtain the results of blood vessel segmentation in retinal images. Convolutional neural networks are part of a machine learning method that processes two-dimensional data. Due to many network levels in CNN, CNN is categorized as a Deep Neural Network. Inspired by the brain's main visual cortex, the CNN structure is the most popular model of deep neural networks for image recognition. The operation itself is similar to conventional imagery, but a significant difference is that studying the supervised learning process is not determined by human experts. When training is successful, the kernel reflects the general facts of the training sample. The conventional CNN philosophy is to discover features through end-to-end training without preprocessing. The step of image enhancement in the retina can be found in systems unable to select humans. The retinal reconstruction structure that remains must produce a total of 12 output features from the color input image, namely the RGB 3 channel [24].

Triwijoyo et al. [25] made a plan for the next research to explore more about various CNN configurations to obtain higher accuracy, such as selecting a training algorithm for fully layered layers connected and using machine learning ensemble. Convolutional Neural Networks (CNN), a variety of deep neural networks, achieve significant success in image processing, achieving advanced performance and accuracy compared to other well-known frameworks[24]. Convolutional Neural Network (CNN) is used as hierarchical feature extraction. Each targeted pixel, the raw pixel value of the rectangular window is centered and immediately provided as CNN input [26].

The Convolutional Neural Network has various architectures, and in this study, the author uses the U-net architecture. U-Net is an architecture that can be used for semantic segmentation, which is the process of classifying each pixel of an image as a class label to understand the image on a per-pixel level. This architecture is very well modified to produce good segmentation in biomedical images. The U-Net architecture is shown in Figure 2.

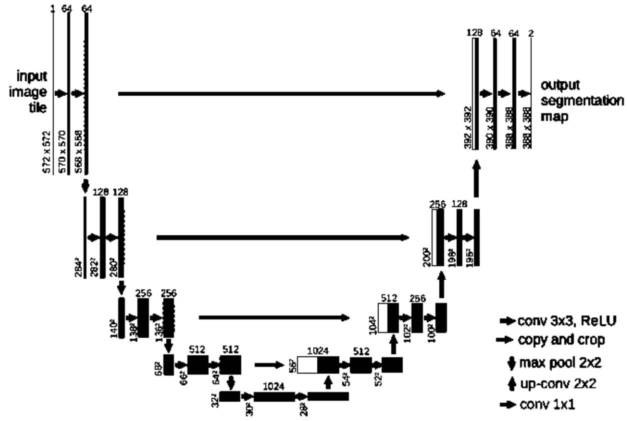


Fig. 2. The Convolutional Neural Network (CNN) U-Net Architecture

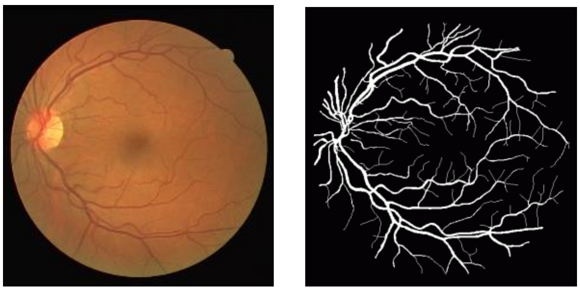
According to Figure 2, the U-Net architecture is in the shape of the letter U. The shape of the architecture is symmetrical and divided into two parts. The left side is called the contracting path, formed by a general convolutional process. The right side is called an expansive path formed by transposed 2D convolutional layers (which can be considered an upsampling technique for now).

IV. Result and Discussion

A. Image Input

As explained in the previous chapter, the researchers used retinal images obtained from the DRIVE (Digital Retinal Images for Vessel Extraction) dataset in this study. The retinal image in the dataset is taken using a special camera or fundus camera. The number of retinal image data used by researchers in this study was 20 retinal images taken from the DRIVE dataset. An example of one of the retinal images from the DRIVE dataset used is shown in Figure 3.

Image input from the DRIVE dataset has a dimension size of 565 x 584 pixels with 96 dpi and a size of 712 KB and uses the .tif format. The image input used must also be of good quality to get good segmentation results. The image shown in Figure 3 is the DRIVE dataset image with the file name 01_test.tif.



(a) (b)

Fig. 3. Sample image from DRIVE database. (a) Original image; (b) Ground truth.

B. Result of Pre-processing

Based on the preprocessing stages, which include Grayscale Conversion, Data Normalized, CLAHE, and

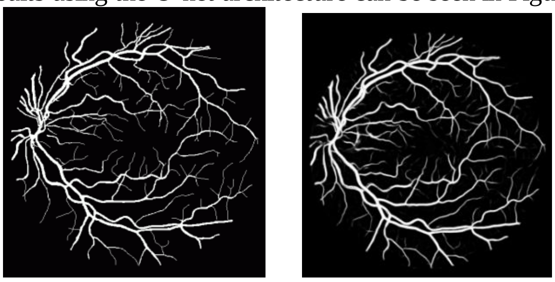
Gamma Adjustments applied to the DRIVE retina image, the results can be seen in Figure 4.

(a) (b)

Fig. 4. Preprocessing result of retinal image. (a) Original image; (b) Preprocessing result.

C. Segmentation

After the retinal image goes through the enhancement or preprocessing stages, the next step is segmentation. Researchers used the Convolutional Neural Network method to obtain segmentation results in this study. Segmentation is the stage of separating objects or determining the background and foreground. In this study, blood vessels will be segmented in retinal images. The DRIVE retinal image segmentation results using the U-net architecture can be seen in Figure 5.



(a) (b)

Fig. 5. Segmentation result. (a) Ground truth; (b) Segmentation result.

Testing is performed with the 20 images of the DRIVE testing dataset, using the gold standard as ground truth. Only the pixels belonging to the FOV are considered. The FOV is identified with the masks included in the DRIVE database.

The ReLU (Rectified Linear Unit) activation function is used in this convolutional neural network. The ReLU activation was an activation layer on the CNN model, which was very effective and simple [27]. The activation function is used to determine whether the result of the network calculation is true or false. The ReLU activation function falls into the category of non-linear activation functions. ReLU is the most used function in almost all deep learning. The ReLU activation function is shown in equation (2).

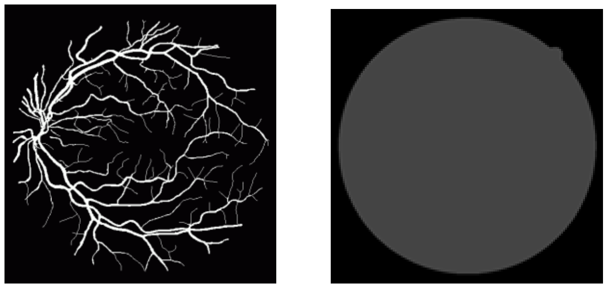
$$R(z)= max(0,z) \tag{2}$$

R(z) will be zero when z is less than zero or equal to zero, and R(z) will be equal to z when z is greater than or equal to zero. Computing using the ReLU activation function is more efficient and faster than the sigmoid activation function.

The sigmoid activation function is more appropriate for a model that predicts the probability as its output because the output is 0 or 1. However, the output is not zero-centered, making it challenging to optimize. Exponential on the sigmoid activation function can also be computed as expensive, expensive in the resource, or long to compute. The segmentation results using the sigmoid function can be seen in Figure 6. The sigmoid function is the most numerous and easy-to-use function in the CNN classification[28].

The sigmoid function was in equation (3).

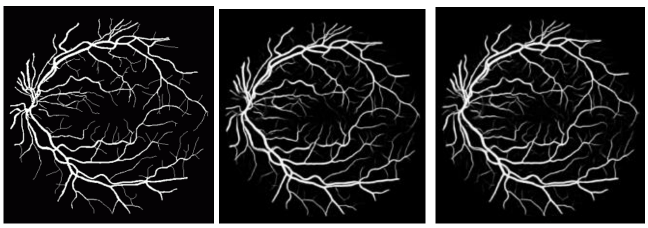
$$z_j = \frac{1}{1+e^{-z\_in_j}} \tag{3}$$



(a) (b)

Fig. 6. Segmentation result with sigmoid function activation. (a) Ground truth; (b) Segmentation result.

Based on the segmentation results in Figure 6, it can be concluded that the sigmoid activation function is not appropriate for the segmentation stage. The appropriate activation function to use is the ReLU (Rectified Linear Unit) activation function. Apart from trying out other activation functions, this research also uses a different kernel size in the U-Net architecture. In the U-Net architecture, the convolutional layer uses a 3x3 kernel size. The results of the segmentation can be seen in Figure 5. In addition to using the 3x3 kernel size, in this study, we tried to use the 5x5 and 7x7 kernel sizes to see the difference. The segmentation results obtained will be shown in Figure 7.



(a) (b) (c)

Fig. 7. Segmentation result with 5x5 kernel size and 7x7 kernel size. (a) Ground truth; (b) Segmentation result with kernel size 5x5; (c) Segmentation result with kernel size 7x7.

D. Discussion

Based on the results above, it can be concluded that the kernel size 5x5 and kernel size 7x7 also produce good segmentation in the retina image, and there is almost no difference because they both achieve the same measurement parameters. The parameter results measured from this segmentation are accuracy, specificity, and sensitivity. Table I shows the parameter results performed on the drive dataset.

Table I. Parameters result of segmentation.

Activation	*Kernel size*	*Acc (%)*	*Sp (%)*	*Sn (%)*	*F1 score (%)*	*Jaccard Score (%)*
ReLU	3x3	95.41	98.43	74.71	80.58	67.48
Sigmoid	3x3	87.27	100	0	0	0
ReLU	5x5	95.48	98.48	74.91	80.84	67.84
ReLU	7x7	95.34	98.45	73.99	80.17	66.90

Table I shows accuracy, specificity, sensitivity, F1 score, and Jaccard score obtained on the DRIVE dataset. Based on the results shown in Table 1 above, it can be concluded that the sigmoid activation function is not appropriate for the segmentation stage. The right activation function used is the ReLU (Rectified Linear Unit) activation function.

The segmentation carried out in the experiments above uses data without augmentation. This study also conducted segmentation experiments using augmented data. The test data, which was originally 20 images, became 80 images to be segmented. The results of the segmentation of blood vessels using augmented data can be seen in Table II below.

Table II. Comparison of a result of segmentation for augmented and non-augmented data with ReLU activation function and kernel size 5 x 5

Data	*Acc (%)*	*Sp (%)*	*Sn (%)*	*F1 score (%)*	*Jaccard Score (%)*
Augmentation	95.48	98.48	74.91	80.84	67.84
Non Augmentation	90.38	90.80	77.53	33.90	20.41

Based on Tables I and II above, evaluate the results using the parameters of accuracy, specificity, and sensitivity. After changing the kernel size value to 5x5 and 7x7, it can be seen that the results are almost the same. The results obtained from segmentation using augmented data are still smaller than segmentation using non-augmented data. The greatest accuracy value is found in the ReLU activation function with a kernel size of 5x5, 95.48%, specificity is 98.48%, and sensitivity is 74.91%. These results indicate that the method used in this study is quite good in obtaining the results of blood vessel segmentation. The better the output and the resulting parameters, the better this method in image segmentation.

Based on Table III, the proposed method approach is tested on DRIVE retina database and obtained better results when compared to other available retina vessel segmentation algorithms.

In addition to using quantitative yield parameters, this study also uses the Precision-Recall Curve and Receiver Operating Characteristic (ROC) Curve to see the segmentation result approach. The ROC curve is a graphical representation of the True Positive Rate (TPR) on the y-axis and the False Positive Rate on the x-axis. The area under the curve (AUC) is an important component in this curve to see the effectiveness of each segmentation approach. The maximum value of the AUC is 1, indicating that the segmentation approach achieves a perfect score for differentiating blood devices from the background. This seems impossible because the number of false positives and false negatives must be zero. While the Precision-Recall Curve is made based on the value that has been obtained from the calculation results with a configuration matrix. The average AUC value is based on the curve in Figure 8.a is 0.9035. The respective precision and recall values obtained from calculating the result parameters are 0.8747 and 0.7471.

Table III. Performance comparison of proposed method with other existing method on DRIVE dataset.

Methods	*Accuracy (%)*	*Specificity (%)*	*Sensitivity (%)*
Proposed Method	95.48	98.48	74.91
Single Convolutional Neural Network [15]	94.54	96.94	75.37
Supervised Feature Learning [29]	94.81	94,93	87.41
Adaptive Thresholding [30]	95.11	-	76.50
Modified ISODATA based on global and local thresholding [17]	95.2	97.2	78
Gumbel Probability Distribution Function-Based Matched Filter [31]	95.22	-	-

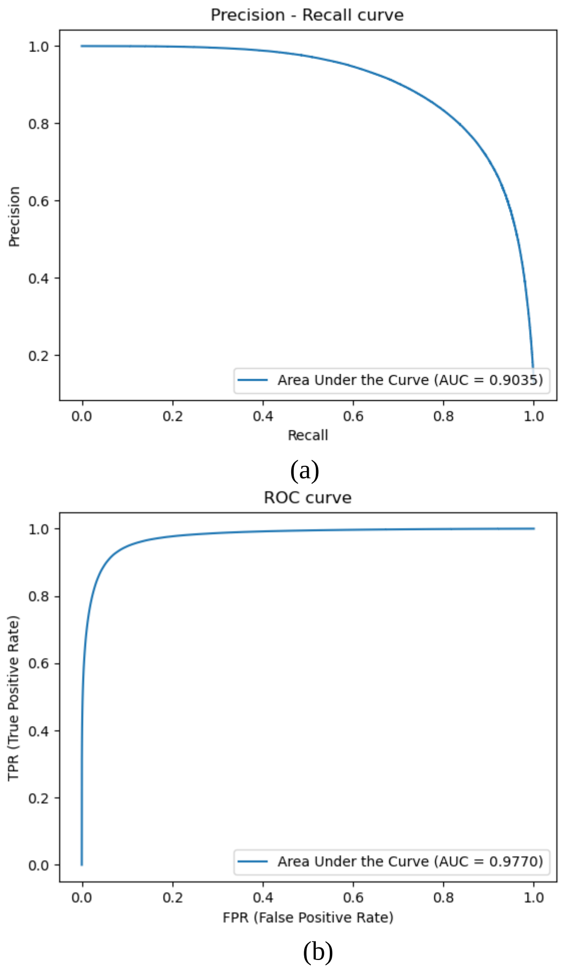
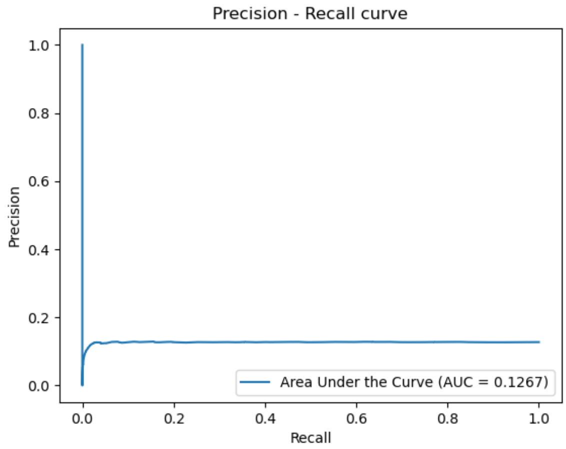
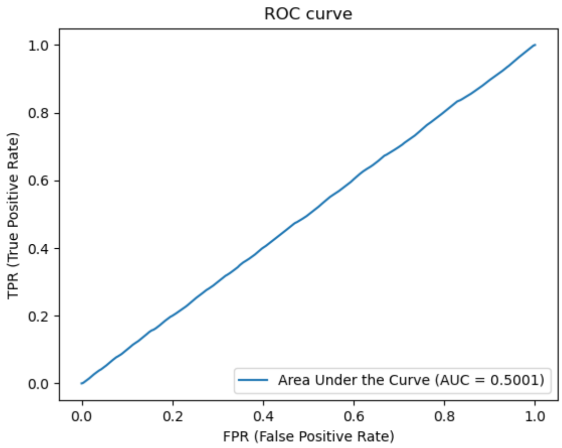


Fig. 8. Curve results from ReLu activation and kernel size 3x3. (a) Precision-Recall curve; (b) ROC curve.

According to on the shape of the curve in Figure 8.b, it can be seen that the curve is good because the curve is close to the point 0.1. The average AUC value is 0.9770. This AUC value close to 1 proves that the performance of the proposed Convolutional Neural Network U-Net is a good method for segmentation of blood vessels in retinal images.



(a)

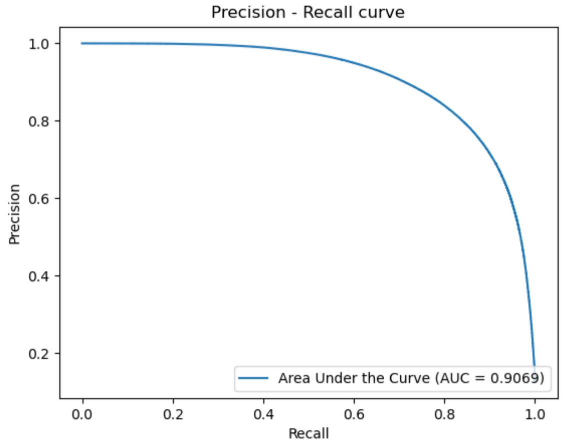


(b)

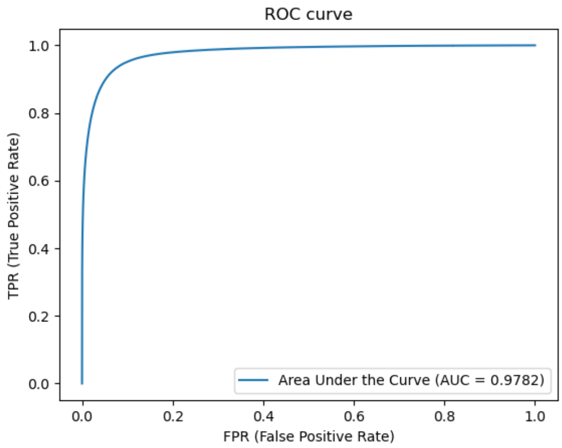
Fig. 9. Curve results from sigmoid activation and kernel size 3x3. (a) Precision-Recall curve; (b) ROC curve.

The average AUC for the above precision-recall curve is 0.1267 in Figure 9.a. This value is considered very small because the precision and recall values obtained from the parameter calculation are zero. Based on the shape of the ROC curve in Figure 9.b, it can be seen that the curve is not good enough because the curve is close to the baseline line or the line that crosses from point 0.0. The average AUC value is 0.5001. The AUC value, which is still far from 1, proves that the performance of the sigmoid activation function is not appropriate to use in the segmentation of blood vessels in retinal images.

The average AUC value based on the curve in Figure 10.a is 0.9069. The respective precision and recall values obtained from calculating the result parameters are 0.8778 and 0.7491. Based on the shape of the curve in Figure 10.b, it can be seen that the curve can be said to be good because the curve is close to the point 0.1. The average AUC value is 0.9782.



(a)



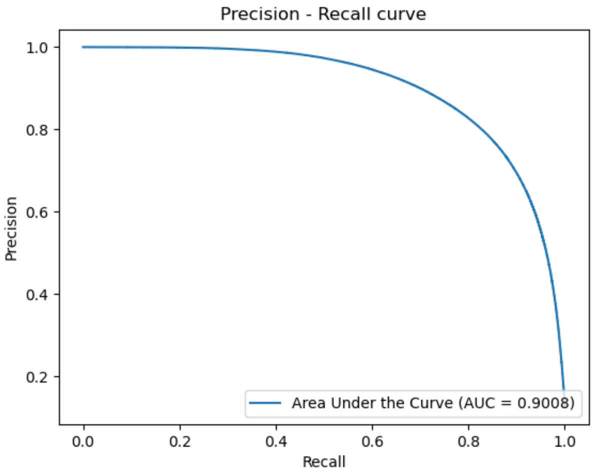
(b)

Fig. 10. Curve results from ReLu activation and kernel size 5x5 a) Precision-Recall curve; (b) ROC curve.

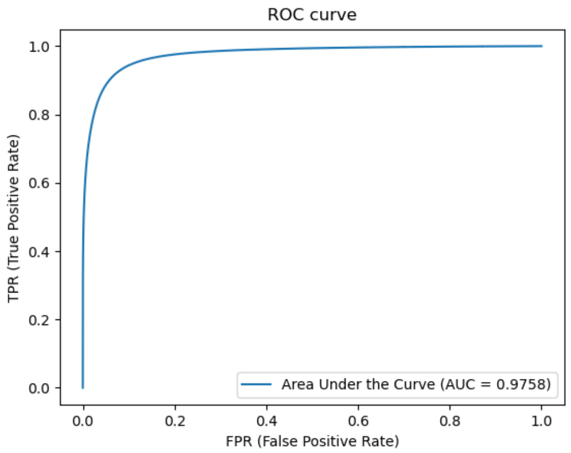
The average AUC value based on the precision-recall curve from Figure 11.a is 0.9008. The respective precision and recall values obtained from the calculation of the result parameters are 0.8747 and 0.7399. Based on the shape of the curve in Figure 11.b, it can be seen that the curve can be said to be good because the curve is close to the point 0.1. The average AUC value is 0.9758.

ROC Curve and Precision-Recall Curve for segmentation using data augmentation are presented in Figure 12. The average AUC value based on the curve in Figure 12.a above is 0.2282. The respective precision and recall values obtained from the parameter calculations are 0.2169 and 0.7753. Based on the shape of the curve in Figure 12.b, it can be seen that the curve can be said to be good because the curve is close to the 0.1 points. The average value of AUC is 0.9328.

Based on this evaluation, it can be concluded that the accuracy value obtained is excellent. This means that the accuracy of a model for segmenting blood vessels is accurate and robust. The resulting specificity value in the proposed method is higher than in some other studies. This shows that the ability of the proposed method to detect retinal blood vessels correctly is quite strong for both thick and thin vessels. The specificity value obtained is higher than the sensitivity value. This means that the model's ability to detect background is superior. The F1-Score value obtained is quite high compared to other methods, meaning that the harmonization between sensitivity and specificity is quite good. This can be seen from comparing the performance results of the proposed method compared to the performance results of the U-Net architecture on Ronnerberger et al. [6].

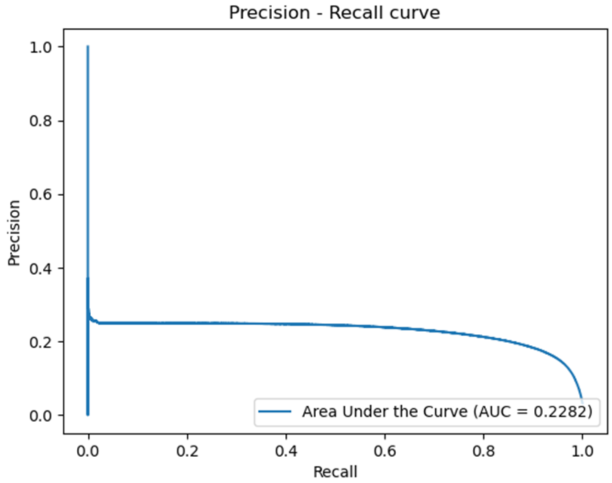


(a)

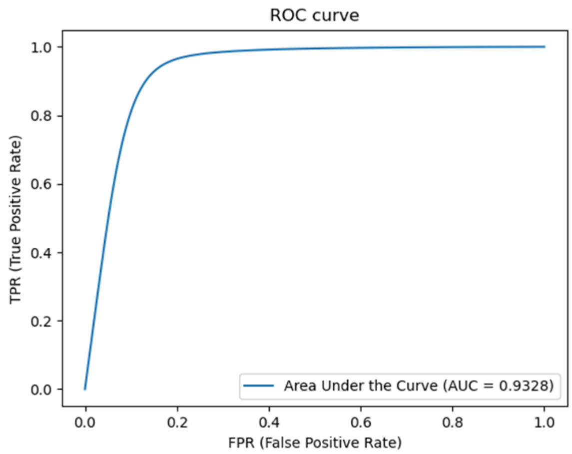


(b)

Fig. 11. Curve results from ReLu activation and kernel size 7x7 a) Precision-Recall curve; (b) ROC curve.



(a)



(b)

Fig. 12. Curve results from Augmentation, ReLu activation, and kernel size 5x5 a) Precision-Recall curve; (b) ROC curve.

V. CONCLUSION

Early detection of retinal disease can be done through the passage of the blood vessels of the retina. Before carrying out the initial diagnosis process on retinal blood vessels, which will be used as an advanced stage for the medical personnel, it is necessary to improve and improve the quality of the retinal image with the final focus on taking the segmentation results from the retinal blood vessels.

U-Net is an architecture of the Convolutional Neural Network that can be used for semantic segmentation, classifying each pixel as a class label to understand the image on a per-pixel level. This architecture is very well modified to produce good segmentation in biomedical images.

The dataset used in this study is the DRIVE dataset. The research results with this method get an accuracy of 95.48%, sensitivity of 74.91%, and specificity of 98.48%. The method used is better and more efficient for image segmentation. The proposed method approach is tested on DRIVE retina database and obtained better results when compared to other available retina vessel segmentation algorithms. Running this program on low-specification hardware will take a very long time.

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