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The Augmentation Data of Retina Image for Blood Vessel Segmentation Using U-Net Convolutional Neural Network Method

Erwin* and Asri Safmi†

Department of Computer Engineering, University of Sriwijaya
Jalan Raya Palembang-Unsri KM 32, Indralaya, Indonesia
**erwin@unsri.ac.id*
†asrisafmi75@gmail.com

Anita Desiani‡ and Bambang Suprihatin§

Department of Mathematics, University of Sriwijaya
Jalan Raya Palembang-Unsri KM 32
Indralaya, South of Sumatera, Indonesia
‡anita_desiani@unsri.ac.id
§bambangs@unsri.ac.id

Fathoni

Department of Information System, University of Sriwijaya
Jalan Raya Palembang-Unsri KM 32
Indralaya, South of Sumatera, Indonesia
Fathoni@unsri.ac.id

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The retina is the most important part of the eye. By proper feature extraction, it can be the first step to detect a disease. Morphology of retina blood vessels can be used to identify and classify a disease. A step, such as segmentation and analysis of retinal blood vessels, can assist medical personnel in detecting the severity of a disease. In this paper, vascular segmentation using U-net architecture in the Convolutional Neural Network (CNN) method is proposed to train a sematic segmentation model in retinal blood vessel. In addition, the Contrast Limited Adaptive Histogram Equalization (CLAHE) method is used to increase the contrast of the grayscale and Median Filter is used to obtain better image quality. Data augmentation is also used to maximize the number of datasets owned to make more. The proposed method allows for easier implementation. In this study, the dataset used was STARE with the result of accuracy, sensitivity, specificity, precision, and F1-score that reached 97.64%, 78.18%, 99.20%, 88.77%, and 82.91%.

Keywords: Diabetic retinopathy; CLAHE; Median Filter; augmentation; U-net; CNN.

*Corresponding author.

1. Introduction

Retina is one of the most important parts of the eye. By proper feature extraction, it can be the first step for a disease to be detected quickly and effectively on retinal image. Commonly detected parts of the retina include blood vessels, optic disk, macula, exudate, and hemorrhage. Of the several parts detected, blood vessels are one of the most important parts of retinal image. The retinal blood vessels consist of arteries and arterioles that, when examined at certain intervals, can help diagnose a disease and can help medical personnel. Therefore, the proper extraction of blood vessels from the retinal image will help reduce dependence on the level of expertise of medical personnel and reduce error factors and shorten the time.[1] In ophthalmology, retinal fundus images play a role in the medical field by diagnosing a disease, for example diabetic, glaucoma, cataracts and others.[2]

Retinal blood vessels are the one of the important structures contained in the fundus retina. Vascular changes are closely associated with many systemic, metabolic, and hematology diseases. Retina vascular morphology can be used to identify and classify the severity of several diseases. A step, such as segmentation and analyzing retina blood vessels, can help medical personnel in detecting these changes. Blood vessel segmentation will produce information about the location of the blood vessels and also the variation in diameter of the existing blood vessels.[3] On the other hand, retina blood vessels can be extracted in several retinal imaging processes to estimate the status of vascular tissue in the retina. The final result obtained from the segmentation will be used as parameter to ensure the performance result of the feature extraction.

In the process of detecting blood vessel on retinal images, there are still difficulties in the formation of blood vessel that are not detected correctly. However, a method increasing contrast and improving retinal image quality is needed so that the results obtained are better, a method that is quite good in improving the quality of retinal images, namely, the Contrast Limited Adaptive Histogram Equalization (CLAHE) method. CLAHE is used to correct problems in the form of low image contrast on a digital image, especially a medical image.[4–9] Then, the Median Filter can also be selected as a method to improve the quality of the retinal image, in the Median Filter, the damaged pixel value will be replaced by the median of the window pixel value.[5,10]

Vascular segmentation of retinal fundus image is one of the powerful methods for diagnosing vascular disease. There are many methods that can be used in the process of segmentation of retinal fundus image, but some of them cannot obtain a good image of retinal vessel segmentation in some thin blood vessels because they are not clearly visible. Currently, deep learning has been widely used in the process of segmentation blood vessels in the retinal fundus and has archived several achievements in terms of classification, detection and segmentation.[2,8,11] Especially, Convolutional Neural Network (CNN) algorithm was selected for retinal fundus image segmentation. CNN is the most commonly used algorithm in computer vision to classify each pixel of the image. CNN showed impressive performance in completing segmentation task and still leaves room for improvement to produce more accurate segmentation.[2,6,7,12–15] CNN is a development of Multilayer Perceptron (MLP) which is designed to process data in the form of images and is included in the Deep Neural Network because of its high network depth and is widely applied to image data. CNN is designed to recognize the visual pattern of an image pixel by going through the pre-processing stage.

CNN is widely used in complex image classification tasks with many class objects with impressive result. One of the most used architectures is U-net architecture which produces good accuracy. It is built on the Fully Convolutional Network (FCN) and modified in such a way to produce better segmentation in medical images. Compared to FCN, U-net architecture is more symmetrical and the skip connection between the down-sampling line and the up-sampling line applies the combined operation rather than summation[2,6,12,13] because U-net architecture is a high-capacity model. An augmentation stage is needed to add training data to avoid overfitting. Augmentation is a step used to study neural networks in the image when the available sample is limited.[8]

In this study, to maximize the result of retinal blood vessel segmentation, we used the step to increase contrast and image quality from grayscale images to get a clear picture of retinal blood vessels using the CLAHE so that the resulting images have more contrast and Median Filter will be used as a step to reduce the noise that is present from the previous contrast enhancement results. Data augmentation is implemented to address the limited number of datasets of image enhancement and quality process before entering the segmentation stage using the U-net architecture of the CNN model.

2. Related Work

Currently, deep learning has been widely used in the research process to segment retinal blood vessels and has archived some great achievements in treating several diseases. For example, Wan *et al.*[11] proposed the feature extraction using deep learning methods such as Alexnet, Vggnet, Googlenet, and Resnet which are the newest CNN methods. By adding normalization and augmentation method to the pre-processing, more datasets will be segmented and a more accurate fundus image will be produced. However, while carrying out the segmentation learning process, it cannot be said to be good because the pre-processing is used only a little.

Dutta *et al.*[10] proposed an approach with several stages to start research, namely, with the pre-processing stage, the image will be extracted to the RGB image which will be taken and converted into grayscale to facilitate the process of removing noise and improving the image for more feature extraction by using two stages, namely, Median Filter and Edge Detection. Feature Extraction and Fuzzy C-Means are used for the filter classification process. Back propagation NN, DNN, and CNN models are used in the post-processing and segmentation stages. However, while conducting training on the dataset, the Back Propagation NN model takes longer and obtains lower accuracy than the DNN and CNN models.

Khan *et al.*[4] proposed techniques which they thought were efficient for segmentation of the retina, namely, CLAHE and MISODATA. CLAHE was chosen in the pre-processing stage as a step to increase contrast in the image and capable to improve image quality as well while MISODATA was used in the segmentation process. However, the performance and research result depend on the stage of cleaning the vessel image which is still considered to have noise. So that all blood vessels that have the same size as the existing noise are eliminated. The segmentation process using MISODATA in this study takes long time when compared to other methods.

Atli and Gedik[8] proposed vascular segmentation using a new model called the Sine-Net that applied up-sampling and down-sampling to capture the features of thin and thick blood vessels. The segmentation image will go through the pre-processing stage using CLAHE and also Multiscale Top Hat Transform (MTHT). Furthermore, the retinal image will be augmented so that a limited number of datasets can be reproduced. But in some metrics, it shows a decline that causes a loss.

Dash and Bhoi[9] proposed the extraction of blood vessels using Gamma Correction and CLAHE. Furthermore, image segmentation will be carried out using Local Adaptive Thresholding and also at the same time the noise cleaning stage using cleaning morphology. The disadvantage of this method is that in some cases pathological image is unable to handle connectivity which can lead to inaccurate result of segmentation.

Cheng *et al.*[6] proposed the U-net method for segmentation of blood vessels in the fundus retinal. The pre-processing stage is performed using the grayscale method to reduce noise and then using Z-score Standardization and CLAHE to increase image contrast and finally using gamma calibration and normalization to adjust the illumination intensity of the image. Finally, the U-net method is used for segmentation. The performance result of the proposed method produces a good performance but there are still deficiencies in the slightly lower accuracy value.

Mostafiz *et al.*[12] proposed two efficient methods for segmentation of blood vessels using a Fuzzy Classifier and U-net autoencoder combined with a residual block. In the fuzzy classifier class, the mean and median of the retinal image for feature extraction is considered and then the fuzzy classifier is used to extract the vessel using statistical values as input and using multi-level and morphological operations. Then in the second method, an autoencoder model is carried out which aims to make the blood vessels more visible. With this method, the accuracy obtained is quite high. But on the part of precision and sensitivity, the accuracy obtained is still low.

3. Proposed Method

The segmentation of blood vessel is an interesting thing to study. Although there have been many studies and method that have been proposed together with better result than before. In this study, the proposed method for segmentation of retinal

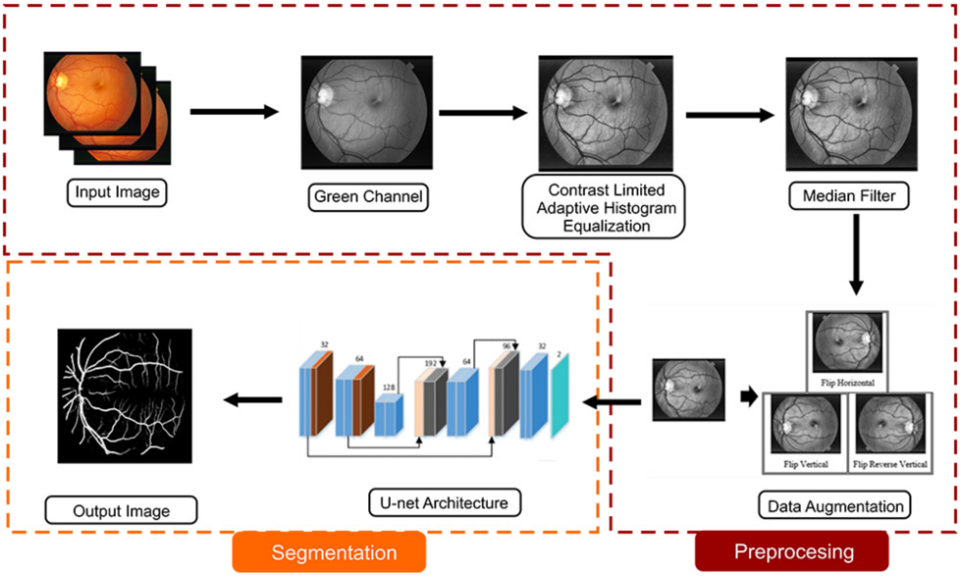


Fig. 1. Flowchart of the proposed method for data augmentation on vascular retinal image segmentation.

vessels here is the U-net architecture of the CNN model. The steps to be carried out consist of two stages, the first step is to improve the image quality by converting the retinal image to each RGB color channel and taking the extraction of green channel which is then followed by increasing the contrast and quality of the image using the CLAHE. To reduce the noise resulting from contrast enhancement of the retinal image, a Median Filter is used for cleaning stage. Next is the phase to increase the limited number of datasets by using rotation augmentation in order to obtain dataset result with various point of views. The last step that will be done is to segment the retinal blood vessels as a result of augmentation.

In this study, 20 retina fundus images were used from the STARE dataset. The following stages of the proposed method are illustrated in Fig. 1.

3.1. *Pre-processing*

The steps taken before extracting blood vessel are the preparation of retinal image data that will be used. The dataset to be used is retrieved from the STARE database. After preparing the retinal image as input, next steps that will be carried out are changing the color, increasing contrast, cleaning noise and increasing the number of datasets so that later performance with high accuracy will be produced. Here are the steps being taken in the pre-processing on the retinal image.

3.1.1. *Green channel separation*

Color channel separation was conducted to produce the image with grayscale with the aim of later image which has separate color channel to be more simple and will get the result of the blood vessel image that was clean from the background image.[16] The output image from the result of this color channel separation will consist of red (R), green (G), blue (B). After this color channel is separated, the green channel was chosen because the resulting image quality was better than the red and blue channels.

3.1.2. *Contrast limited adaptive histogram equalization*

CLAHE was used as a developer in an imaging process in medical terms which later will give good result in improving the quality and contrast of an image. Increasing contrast can be done by using the Adaptive Histogram Equalization (AHE) and Histogram Equalization (HE) methods.[4] After performing the green channel separation stage, next step is to improve the contrast using CLAHE. In the retinal image that has been generated from the previous stages, there are still difficulties in differentiating the contrast between blood vessels and non-vessels. CLAHE was chosen as a method with the aim of increasing contrast and minimizing noise in the image to increase the contrast of the retinal image for the parts that have low contrast improvement method from the previous method. CLAHE limits the amplification by cutting the limits of the histogram values. The values of the histogram are also called the clip limit.

3.1.3. *Median Filter*

Median Filter is a nonlinear digital filter technique, which is often used to remove noise in an image. Median Filter was chosen as a method to reduce noise in the image while maintaining existing details such as image edges for better feature extraction. Median Filter works by calculating the middle value of the calculated result with the pixels in the image being considered.[5]

3.1.4. *Data augmentation*

Augmentation is the process of increasing the size and quality of a limited number of training datasets. Augmentation is a very important step for studying neural network in images when the available samples are limited. Because the U-net architecture is a high-capacity model, an augmentation stage is needed to add training data to avoid overfitting. The augmentation performed on the Median Filter retinal image is rotational augmentation which aims to increase the diversity of retinal image data. Augmentation techniques include horizontal flip, vertical flip, and vertical reverse flip in the following equations:

$$\text{flip horizontal} = \begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} -x \\ y \end{bmatrix}, \tag{1}$$

$$\text{flip vertical} = \begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} x \\ -y \end{bmatrix}, \tag{2}$$

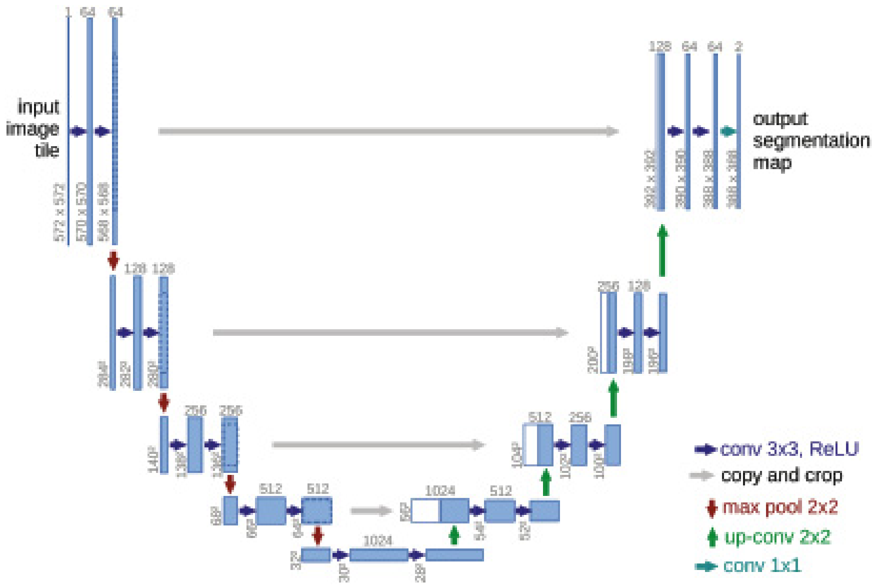


Fig. 2. U-net architecture by Ronneberger *et al.*

$$\text{flip reverse vertical} = \begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} x \\ -y \end{bmatrix} = \begin{bmatrix} -x \\ y \end{bmatrix}. \tag{3}$$

3.1.5. *U-net architecture*

U-net Architecture is one of the CNN's deep learning methods that is most often used in the image segmentation stage. The U-net architecture was introduced by Ronneberger *et al.* in 2015 with the aim of assisting the biomedical segmentation process.[13] Figure 2 describes the U-net architecture which is divided into three parts as follows:

(1) The contracting/ down-sampling route
(2) Bottleneck
(3) Expanding/ up-sampling path

Contracting or down-sampling consists of 4 blocks and each block is composed of a 3×3 convolution layer plus an activation function and 2×2 max pooling. It should be noted that the feature maps will be doubled for each pooling, starting with 64 feature maps in the first block and 128 for the second block. Contracting aims to capture the context of the input image in order to segment it. This contextual information is then transferred to the up-sampling path by means of a skip connection.

Bottleneck is the part between the up-sampling and down-sampling paths. The bottleneck is constructed from only two convolutional layers (with batch normalization).

Expanding or up-sampling has the aim of allowing proper localization combined with contextual information from the contracting path consisting of 4 blocks and each block consisting of a deconvolutional layer with two strides, merging with a feature map that is cut from the contracting path, and a 3×3 convolution layer plus an activation function (with batch normalization).

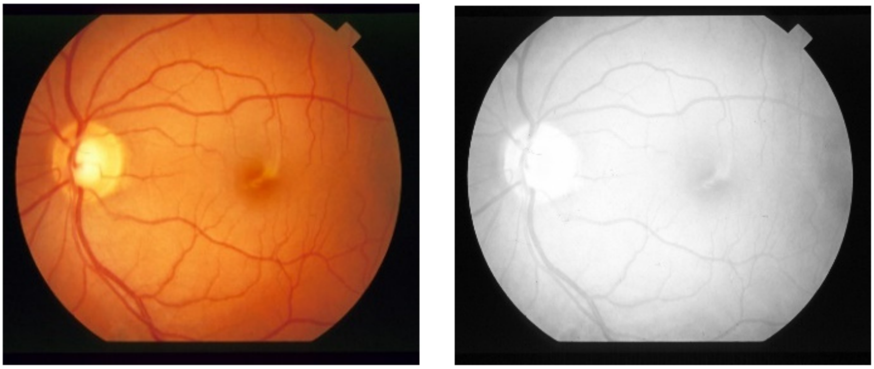
4. Experiments and Result

In this study, we used a Spyder which is a numerical computation scope with a python-based programming language with Intel Core i9-9900 processor specification, 3.50 Hz CPU's, Nvidia GeForce RTX 2080 Graphic Adapter with 32 RAM. The initial retinal fundus image dataset was 20 from the STARE retinal fundus database. The parameters used in U-net are presented in Table 1.

We have performed retinal image analysis and segmentation using the extracted green channel, where the color channel separation process is divided into three color channels with different values for each color channel. In Fig. 3, it can be seen that the comparison between the three colors channels is clearly different. In Fig. 3, (a) is input from the initial image, (b) is the extraction result from the red channel, (c) is

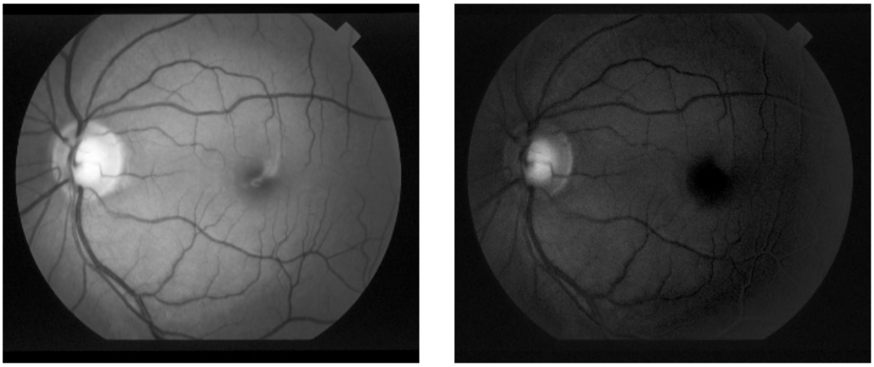
Table 1. U-net parameters used in this study.

Modal Parameters	Fill in Parameters
Hidden layer activation	Relu
Layer output activation	Sigmoid
Optimization	Adam
Learning rate	0.00001
Epoch	500
Batch size	32
Input layer	256,256,1



(a) (b)

Fig. 3. (a) Original image, (b) red channel, (c) green channel, (d) blue channel.



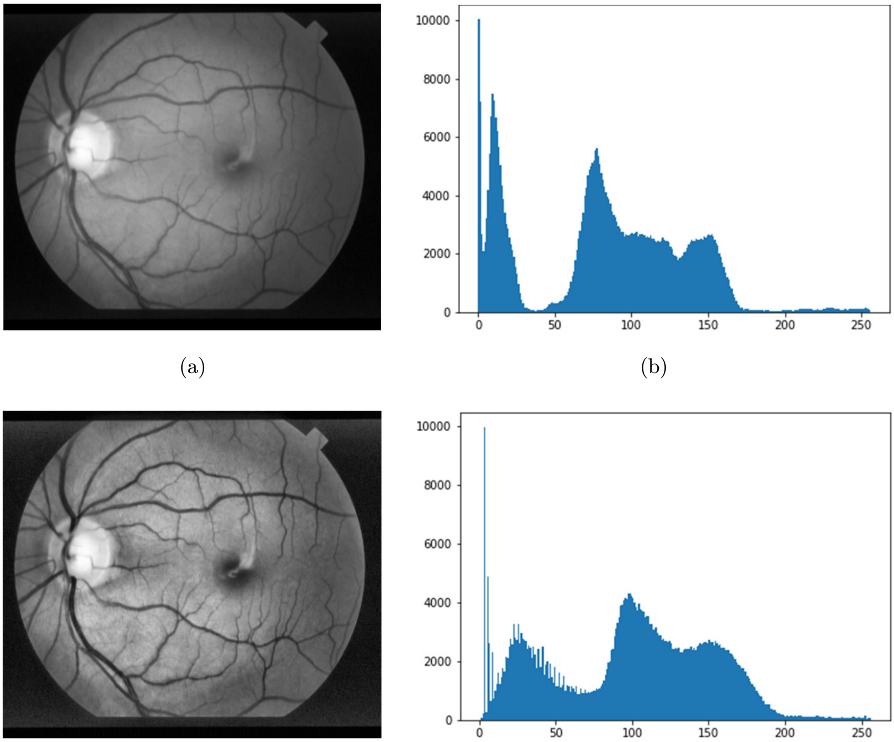
(c) (d)

Fig. 3. (*Continued*)

the extraction result from the green channel, (d) is the result of the extraction of the blue channel. In the red channel result, the resulting output image has a color contrast that is too bright, causing undetectable parts of the blood vessels. Then in the green channel result, the resulting output image is very good and makes parts of the blood vessels in the retinal image clearly visible. Furthermore, in the blue channel, the resulting output image has too dark contrast and causes not all the veins to be visible and it can be concluded that the green channel can be selected because the resulting output image is very clear compared to other two color channels.

After separating the green channel, the next step is to increase the contrast in the parts of the blood vessels that are less clear which will affect the calculation parameters. In Fig. 4, (a) is the result of green channel before the contrast and image quality is enhanced, (b) is the result of the histogram before the increase in contrast and image quality, (c) is the result of improved contrast and vascular quality in retinal images, (d) is a histogram of the result of increasing contrast and image quality. It can be seen in Figs. 4(a) and 4(b) that the resulting images from the color channel separation stage still produce some vague visible parts of the blood vessels with an unstable histogram at each pixel. Then by using the CLAHE method, each pixel will be increased wherein the contrast of each part will be strengthened and the parts will be fixed that should be usable so that the output image histogram parameter will produce a clearer image with blood vessels, as in Figs. 4(c) and 4(d).

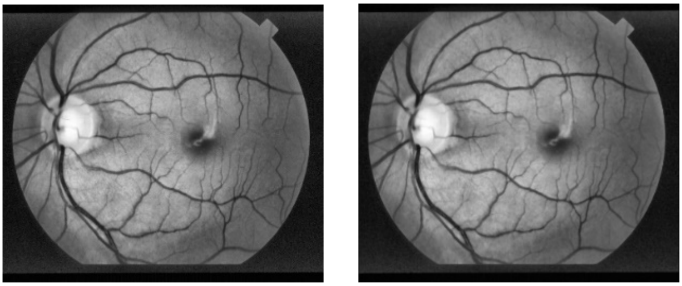
The next step is cleaning the CLAHE image from noise using the Median Filter. At this stage, the Median Filter will clean the small pixel obtained from the result of the contrast enhancement using the previous CLAHE. In Fig. 5, (a) is the original image resulting from CLAHE and (b) is the image resulting from the Median Filter. In the result of contrast enhancement using CLAHE in Fig. 5(a), the resulting output image is proven to be good, but the image still produces a lot of noise. To reduce the



(a) (b) (c) (d)

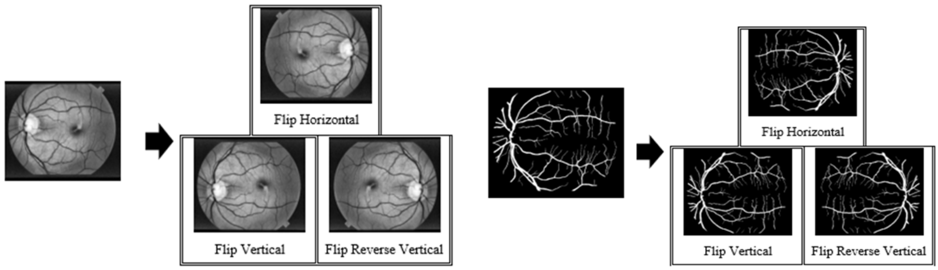
Fig. 4. (a) Green channel, (b) histogram of the green channel, (c) CLAHE image, (d) histogram of the CLAHE image.

amount of noise, Median Filter was chosen because it can increase the clarity of an image and reduce noise so that the resulting image is smoother by replacing the damaged pixel value and fixing it as in Fig. 5(b).



(a) (b)

Fig. 5. (a) CLAHE image and (b) image after Median Filter.

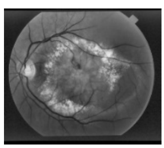
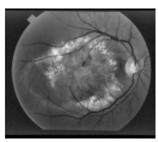
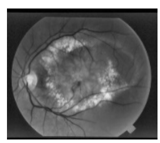
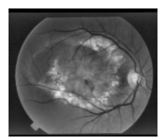
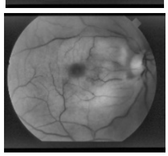
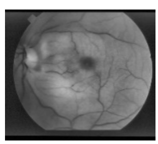
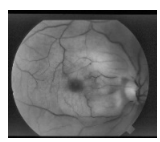
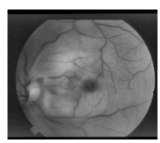
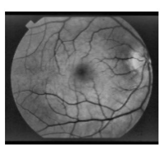
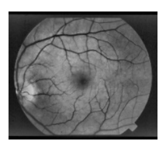
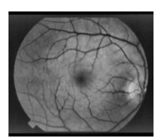
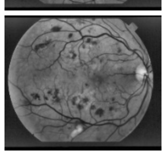
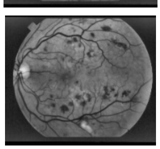
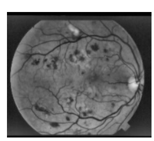
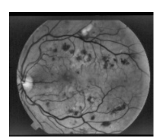
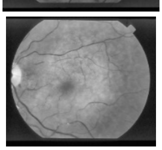
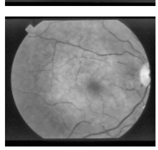
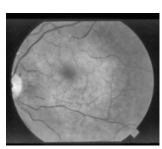


(a) (b)

Fig. 6. (a) Image augmentation of Median Filter result (b) Image augmentation of Adam Hoover's ground truth.

After enhancing and repairing the retinal image, the next step is augmentation. Augmentation was carried out on the STARE dataset from Adam Hoover's ground truth result. Augmentation used rational augmentation consisting of flip horizontal, flip vertical, and flip reverse vertical. In Fig. 6, (a) is an example of augmentation

Table 2. Image augmentation of Median Filter result.

No.	File Name	Median Filter Result	Flip Horizontal (H)	Flip Vertical (V)	Flip Reverse Vertical (RV)
1.	Im0002				
2.	Im0004				
3.	Im0081				
4.	Im0139				
5.	Im0319				

result from the median filter wherein the image augmentation dataset is the result of retinal image repair using the Median Filter method consisting of 20 image data, then rotated vertically to produce 20 new data, then the Median Filter dataset is rotated horizontally to produce 20 new data and last dataset rotates reverse vertical to produce 20 new datasets with total number of augmentation result in the Median Filter dataset which is 80 data and can be seen in Table 2. Next in Fig. 6, (b) is an example of the augmentation of ground truth Adam Hoover, where the augmentation stage carried out is the same as the augmentation stage in the previous Median Filter dataset. The dataset of Adam Hoover ground truth consists of 20 black and white image data, first rotated vertically to produce 20 new datasets, then rotated back horizontally to get 20 horizontal datasets, and finally rotated reverse vertically to get 20 datasets with the total number of ground truth datasets, namely, amounting to 80 data and can be seen in Table 3.

The next stage is segmentation of blood vessels from the result of previous processing. After passing through the data augmentation stage, the current dataset is 80 for image enhancement and 80 for ground truth. Furthermore, the retinal image

Table 3. Image augmentation of Adam Hoover's ground truth.

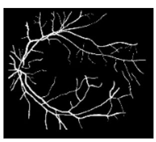
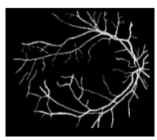
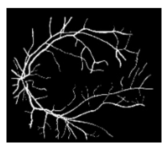
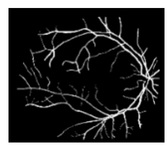
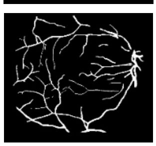
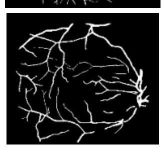
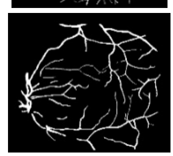
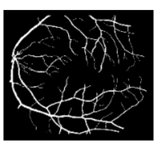
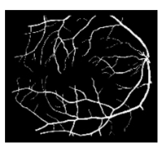
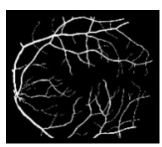
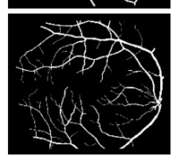
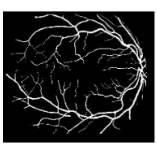
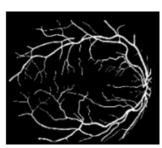
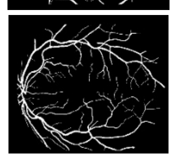
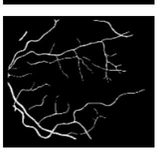
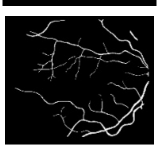
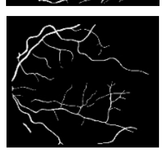
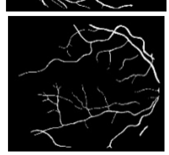
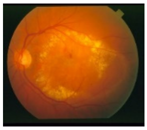
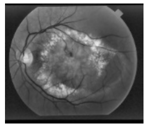
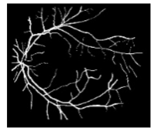
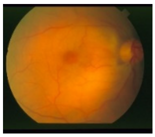
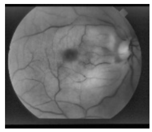
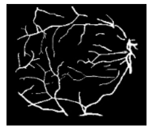
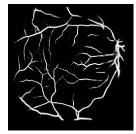
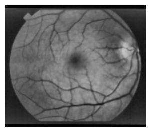
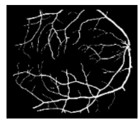
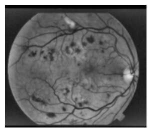
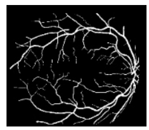
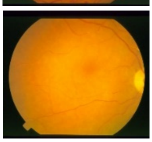
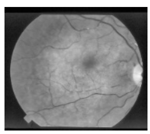
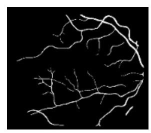
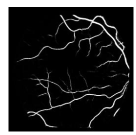
No.	File Name	Ground Truth	Flip Horizontal (H)	Flip Vertical (V)	Flip Reverse Vertical (RV)
1.	Im0002				
2.	Im0004				
3.	Im0081				
4.	Im0139				
5.	Im0319				

Table 4. U-net segmentation result from STARE dataset.

No.	File Name	Original Image	Pre-Processing	Ground Truth Adam Hoover	Segmentation Result
1.	im0002				
2.	im0004				
3.	H_im0081				
4.	V_im0139				
5.	RV_im0319				

segmentation process was previously divided into 80% training data and 20% testing data. The segmentation result of the U-net architecture can be seen in Table 4.

After obtaining the result of segmentation using the U-net architecture, the next step is to conduct an evaluation. Following are the results of retinal image segmentation using U-net architecture with epoch 500, batch size 32 and the loss function used is binary cross-entropy. In Figs. 7 and 8, it can be seen that the accuracy and lost values in the model show pretty good result.

In Fig. 7, epoch used is 500 and it can be seen that the increment value for training data and testing data increases regularly and there is a significant increase at epoch 90 toward 100. The results obtained on the accuracy model are from epoch 100 to 500, which show very good result.

In Fig. 8, the loss model used is binary cross-entropy with a fair good loss result, indicated by the average results of training and testing data that drop regularly and no value increases too significantly.

The next step is an important calculation which is made to determine the suitability of the image based on the existing ground truth of the proposed method so that it is known how good the result of the research have been. The method used is matching based on the ground truth dataset STARE with a confusion matrix.

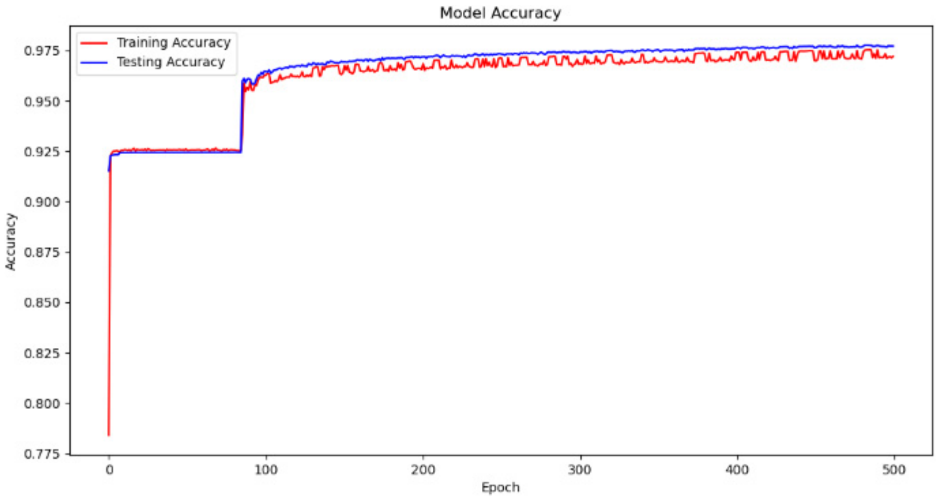


Fig. 7. Graph of training and testing process accuracy.

Measurement parameters to be searched for are accuracy, sensitivity, specificity, precision, and F1-score using the following equations:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FN} + \text{FP}}, \tag{4}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \tag{5}$$

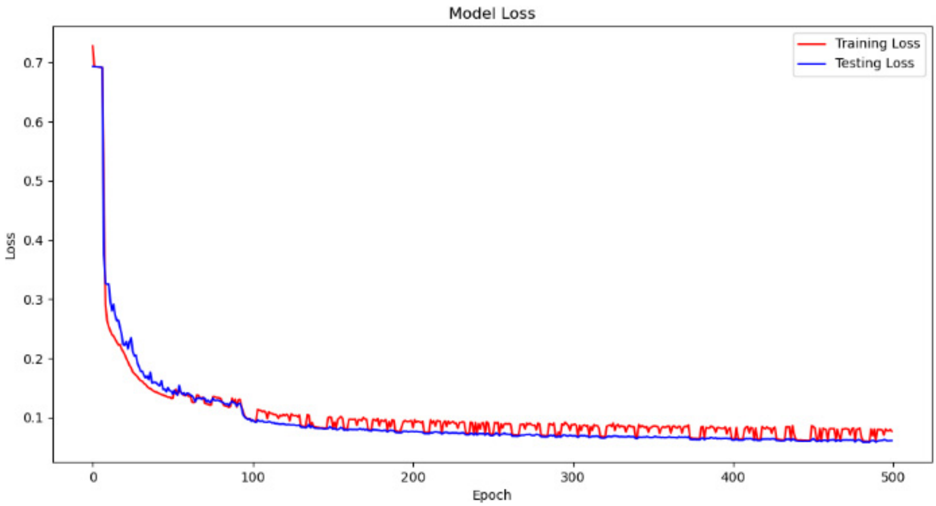


Fig. 8. Loss graph of the training and testing process.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}, \tag{6}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \tag{7}$$

$$\text{F1-score} = \frac{2\text{TP}}{2\text{TP} + \text{FP} + \text{FN}}, \tag{8}$$

where

- TP (True Positive) is the number of positive images that are matched and classified according to the dataset correctly by the system.
- TN (True Negative) is the number of negative images that are matched and classified according to the dataset correctly by the system.
- FN (False Negative) is the number of negative images that are matched based on the wrong dataset by the system.
- FP (False Positive) is the number of positive images that are matched based on the wrong dataset by the system.

Based on the result of these parameters, accuracy, sensitivity, specificity, precision, and F1-score of the segmentation of retinal vessel are obtained using the STARE dataset.

Based on Table 5, it can be seen that evaluation of the result parameter from the STARE dataset using Adam Hoover's ground truth includes accuracy, sensitivity, specificity, precision, and F1-score. The value obtained from each result parameter is 97.64% for accuracy, 78.18% for sensitivity, 99.20% for specificity, 88.77% for precision, and 82.91% for F1-score. From the results that have been obtained, it can be seen that the calculated results for the accuracy and specificity parameters of the proposed method produce a relatively high value because the resulting input image can be detected properly by the system. Then the precision and F1-score obtain pretty good result with quite high results. The value that still needs to be improved is the sensitivity value which is still relatively low. Meanwhile, the results of comparisons made by the previous researches are listed in Table 6, where the results have outperformed the methods proposed by other researchers in the parameters of accuracy, specificity, and precision. However, the sensitivity parameter is still relatively low compared to other researchers and still needs to be re-tested.

The following is a comparison table between the previously proposed method and other methods used by the previous researchers.

Table 5. Parameter of accuracy, sensitivity, specificity, precision, and F1-score.

	Parameter				
Dataset	Accuracy	Sensitivity	Specificity	Precision	F1-Score
STARE	97.64%	78.18%	99.20%	88.77%	82.91%

Table 6. Comparison of segmentation result from the proposed method with the previous method.

Method	Accuracy	Sensitivity	Specificity	Precision	F1-Score
Khan *et al.*[4]	95.7%	74.5%	97.4%	—	—
Soomro *et al.*[14]	96.8%	84.8%	98.6%	—	—
Mostafiz *et al.*[12]	95.37%	55.82%	98.62%	86.22%	—
Atli and Gedik[8]	96.89%	79.87%	98.54%	—	—
Proposed Method	**97.64%**	**78.18%**	**99.20%**	**88.77%**	**82.91%**

5. Conclusion

In this study, the blood vessel segmentation of the retinal image was carried out using U-net architecture assisted by the data augmentation method using the STARE dataset and the results obtained were 97.64% accuracy, 78.28% sensitivity, 99.20% specificity, 88.77% precision, and F1-score 82.91%. From these results, it is indicated that the proposed method produces more advantages than the method proposed by the other researchers. The combined use of CLAHE and Median Filter produces a good output image in terms of enhancing the contrast and quality of the blood vessels.

The augmentation method is very helpful in the pre-processing stage before performing segmentation using U-net architecture. With augmentation, the training process can be maximized and overfitting can be avoided. From the result shown, it explains that the U-net architecture with the proposed method can be used in the medical world, especially in the field of blood vessel segmentation. For future work, it is hoped that the result of the parameters of sensitivity can be increased so that later the result obtained will be better.

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