

## The Hybrid Method of SOM Artificial Neural Network and Median Thresholding for Segmentation of Blood Vessels in the Retina Image Fundus

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# The Hybrid Method of SOM Artificial Neural Network and Median Thresholding for Segmentation of Blood Vessels in the Retina Image Fundus

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## Abstract

Blood vessels in the retina of the eye are one important sign when making a diagnosis of hypertensive retinopathy. On the retina can be known several signs including tortuosity and arteriovenous ratio. Blood vessels mixed with a number of objects in the retina, the segmentation of blood vessels becomes a very interesting challenge because they have to separate blood vessels from a number of objects. This study aims to segmentation blood vessels using the main method of self-organizing maps artificial neural networks (SOM-ANN). The proposed segmentation method is divided into three stages, namely preprocessing, segmentation, and performance analysis. The preprocessing step is to improve image quality using the contrast-limited adaptive histogram equalization (CLAHE), median filter, and morphology. The segmentation stage uses the SOM-ANN algorithm combined with the mean or median thresholding. The performance parameters which are measured consist of sensitivity, specificity, and area under the curve (AUC). The test results using the dataset STARE and DRIVE show that the median thresholding is able to provide the best AUC performance compared to the mean thresholding. The proposed segmentation model is able to provide performance in the excellent category, with AUC values of 90.55% for the STARE dataset and 90.35% for the DRIVE.

**Keywords:** Segmentation, Blood vessel, Retinal, SOM-ANN, Thresholding

## 1. Introduction

Hypertension retinopathy is diagnosed by observing the retina of the eye. Observations were made using a fundus camera. Accuracy in observations is very dependent on the experience of a clinician. The more experienced, the faster and more precise in the diagnosing. The development of information technology has brought changes in health services including in diagnosing the disease [1], one of them is the diagnosis of hypertension retinopathy. This diagnosis is made by analyzing the retinal image produced from the fundus camera. Retinal image analysis is performed using a number of stages, one of which is segmentation. This process is the separation of objects that will be observed for diagnosis with the background. Diagnosis of hypertension retinopathy is done by analyzing blood vessels, so that segmentation is done by separate blood vessels from the background.

A number of studies have segmented retinal blood vessels with various methods. The

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segmentation method in a number of studies uses many approaches including clustering and thresholding. The clustering method is a data mining technique for grouping data into groups of data that are close together in one group [2]. Clustering has a number of algorithms such as k-means, fuzzy c-means (FCM), possibilistic FCM, and self-organizing maps artificial neural networks (SOM-ANN). The case of image segmentation by clustering it is necessary to anticipate several data characteristics including overlapping data so that the results of segmentation produce a clear difference between objects and backgrounds. A number of studies have shown that the k-mean algorithm is not good for overlapping data cases. This is as explained in the research of Budayan et al. [3]. The research explains that the SOM neural network algorithm and FCM are better able to overcome overlapping data problems.

Previous studies that segmented retinal blood vessels using FCM were Dey et al. [4]. In this study, FCM has not been able to show good performance, namely by producing a very low specificity value, so the AUC value is still below 80%. This is different from research conducted by Supot et al. [5]. In this study using fuzzy k-means, which has a process similar to the FCM, but is able to provide improvements to the specificity parameter, so that the AUC value can reach 87.87%. The next study using FCM for segmentation was conducted by Memari et al. [6]. The study was able to provide good performance with AUC 87%, unfortunately, the research produced too low sensitivity below 80%. The same AUC value was also generated in the study of Kar and Maity [7]. In addition to the two studies, a combination of FCM with entropy information was developed by Mapayi et al. [8] and weighted FCM by Kande et al. [9]. Mapayi et al. [8] only mentioned the high accuracy generated, while Kande et al. [9], only mentioned having a better performance than the global thresholding.

The development of clustering for blood vessel segmentation does not stop at FCM, but also in combination with a number of algorithms, such as Lupascu and Tegolo [10]. The study used SOM-ANN and k-mean for retinal blood vessel segmentation, the results were able to provide a relatively high AUC value compared to segmentation with FCM, which is 83.323%. Another combination was also carried out by Hassanien et al. [11], which combines FCM with artificial bee colony optimization (ABC). The combination also gives a relatively low performance for the sensitivity parameter, so that the AUC parameter reaches only 84.6%. The research of Hassanien et al. [11] is no better, compared to segmentation that only uses FCM. The research of Hassanien et al. [11] is also no better than a

combination of SOM-ANN hybrids with k-means. This shows that the combination of several methods does not guarantee an increase in performance.

Referring to a number of previous studies, this study proposes a segmentation model that combines SOM-ANN and thresholding methods. The thresholding method used is mean and median. Mean thresholding uses the threshold value obtained from the average the center of cluster produced, while the median thresholding uses the median value from the center of the cluster. Before the segmentation process begins with pre-processing which aims to improve image quality and optic disc removal. The optical disc removal is intended so that the optical disc is not translated as a blood vessel in the segmentation process. Performance analysis is done by referring to the resulting confusion matrix table. The performance parameters which are measured consist of sensitivity, specificity, and area under the curve (AUC). Statistical tests were also carried out, to find out the effect of the mean thresholding and median thresholding methods.

## 2. Methods

This study uses the DRIVE [12] and STARE [13] datasets for the testing process. Both datasets can be obtained online. Each dataset consists of 20 retina fundus images that have not been segmented and 20 retinal fundus images that have been segmented manually. In this study, retinal blood segmentation was carried out using the method shown in Figure 1. The study was divided into three stages, namely preprocessing, segmentation, and performance analysis.

The preprocessing stage is carried out a number of processes to improve the quality of the retinal image, and the remove of the optic disc. The quality improvement was carried out using a number of methods namely contrast-limited adaptive histogram equalization (CLAHE) [14], morphology [15] and median filter. Morphology operations performed using the opening method. The next step is the removal of the optic disc, the process aims to prevent the optic disc from being translated as blood vessels, which in turn can affect system performance. Optic disc removal is done by subtracting the retinal image of the repaired results with its inverse. The next process is segmentation. The segmentation process is preceded by reshape of the retinal image matrix. The reshape process is the converts of the retinal image matrix from a 2-dimensional to the 1-dimensional, which then becomes the SOM-ANN input. This makes the clustering process using only one attribute.

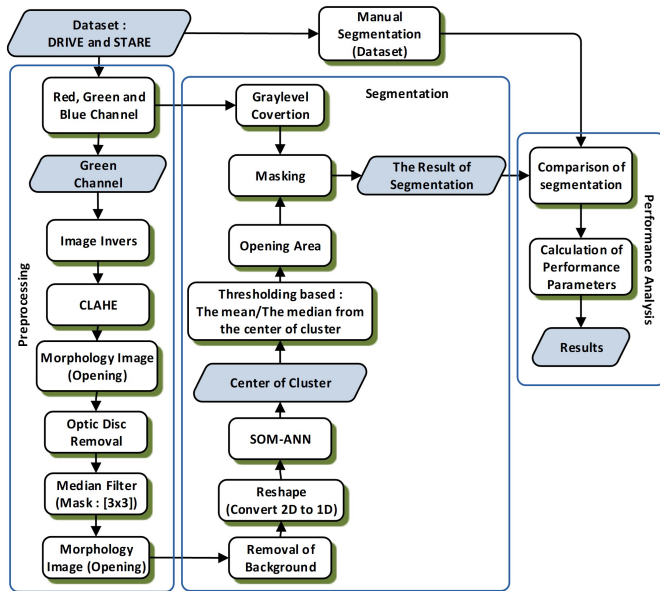


Figure 1. Research method.

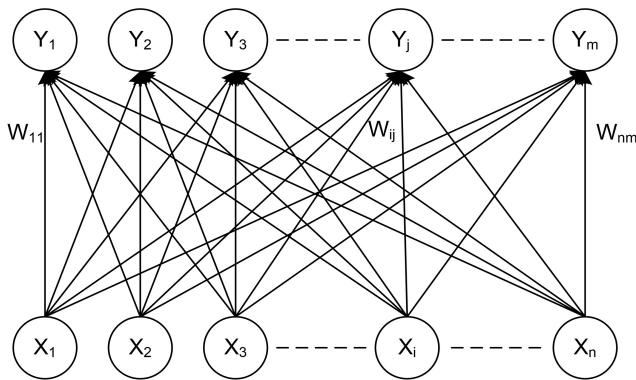


Figure 2. The architecture SOM-ANN.

The main algorithm for segmentation is SOM-ANN. The algorithm is widely used for clustering, but it is also well known in visualization to project complex relationships from high-dimensional input space to low-dimensional input space. The output of SOM-ANN is a node where nodes that have similarities to each other will be close together, while nodes that are less similar will be located far apart [16]. The SOM-ANN has an architecture as shown in Figure 2 [17]. The SOM-ANN algorithm has a number of steps outlined below:

- Step-1: Determine the weight of the  $W_{ij}$  network randomly (centroid), the neighbor parameter  $R$ , the value of the learning rate, the number of clusters ( $m$ )
- Step-2: For each  $X_{ij}$  data, do steps in Step-3 to Step-8 until there is no weight update.

- Step-3: For each  $j$  do the calculation :

$$D(j) = \sum_i (w_{ij} - x_i)^2. \quad (1)$$

- Step-4: Find the minimum value of variable  $j$  from  $D(j)$ .
- Step-5: For all units of  $j$  that are within radius  $R$  of  $j$  then for all  $i$  do :

$$w_{ij}(new) = w_{ij}(old) + \alpha[x_i - w_{ij}(old)]. \quad (2)$$

- Step-6: Update learning rate.
- Step-7: Reduction radius of the topological neighborhood at specified times.
- Step-8: Test stopping condition.

The steps were taken after SOM-ANN is thresholding. The thresholding process is carried out by referring to the center of the cluster generated from the SOM-ANN. The thresholding (Th) process is done using two methods, namely the mean and median as shown in Eqs. (3) and (4).

$$Th_{mean} = \frac{\sum_{j=1}^m w_j}{m}, \quad (3)$$

$$Th_{median} = \begin{cases} w_{\frac{m+1}{2}}, & \text{if } m \text{ odd,} \\ \frac{w_{\frac{m}{2}} + w_{\frac{m}{2}+1}}{2}, & \text{if } m \text{ even.} \end{cases} \quad (4)$$

The mean method uses the average cluster center threshold generated by SOM-ANN, while the median method uses the median value. The threshold value is used to determine the blood vessels or background. If the pixel value of the retinal image exceeds the threshold value, then it is translated as a blood vessel, whereas if it is less than the threshold value then it is translated as background. The next step is morphology surgery, which is by the opening method. The last stage is the calculation of performance. The performance is measured using parameters of sensitivity, specificity, and the AUC by referring to the confusion matrix table as shown in Table 1. Referring to Table 1, the performance parameters can be written in Eqs.

Table 1. Confusion matrixs

Actual class	Predictive class	
	Positive	Negative
Positive	TP	FN
Negative	FP	TN

(5)–(7).

$$\text{Sensitivity} = \text{SEN} = \text{TP}_{\text{rate}} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \quad (5)$$

$$\text{Specificity} = \text{SPE} = \text{TN}_{\text{rate}} = \frac{\text{TN}}{\text{TN} + \text{FP}}, \quad (6)$$

$$\text{AUC} = \frac{1 + \text{TP}_{\text{rate}} - (1 - \text{TN}_{\text{rate}})}{2}. \quad (7)$$

### 3. Analysis

The performance of the results of tests conducted using the STARE dataset is shown in Table 2. Testing is carried out on the segmentation model using hybrid SOM-ANN and thresholding. The thresholding method used is mean and median. Table 2 shows that the average of 20 test data shows that the performance of the hybrid SOM-ANN method with median thresholding is better than the mean thresholding. The me-

dian thresholding method, the best performance occurs in the number of clusters 5, while the mean method in the number of clusters are 8.

The best conditions for test the mean and median thresholding methods are performed using the statistical method. Tests carried out using 20 data. The results of the tests conducted can be shown in Table 3. Table 3 shows that the p-value <0.05 which means that the median thresholding is significantly better than the mean thresholding. This result is also strengthened by the number of clusters for the median thresholding is smaller than the median thresholding. This makes the median thresholding has a computational time for segmentation much shorter than the mean thresholding. This shows that the combination of SOM-ANN with the median thresholding is able to provide performance with AUC values above 90% and included in the excellent category [18].

Tests using the DRIVE dataset give results as shown in Ta-

Table 2. Performance test results with the STARE dataset

Cluster	Method of thresholding					
	Mean			Median		
	SEN (%)	SPE (%)	AUC (%)	SEN (%)	SPE (%)	AUC (%)
2	75.020	96.570	85.800	75.020	96.570	85.800
3	76.920	96.620	86.770	88.300	92.320	90.310
4	76.570	96.630	86.600	86.180	93.400	89.790
5	78.420	96.310	87.360	90.500	90.670	90.590
6	79.460	96.010	87.730	90.690	90.200	90.450
7	81.220	95.550	88.380	93.090	87.010	90.050
8	82.470	95.150	88.810	93.660	86.170	89.920
9	82.900	94.640	88.770	93.250	86.120	89.680
10	82.830	94.720	88.770	93.680	84.870	89.280

Table 3. Statistical test results for the dataset of STARE and DRIVE

	STARE		DRIVE	
	Mean	Median	Mean	Median
Mean	0.88810	0.90586	0.89083	0.90349
Variance	0.00102	0.00059	0.00042	0.00023
Observations	20	20	20	20
df	19		19	
t Stat	-4.82593		-4.8668	
p(T<=t) one-tail	0.00006		0.00005	
t Critical one-tail	1.72913		1.72913	
p(T<=t) two-tail	0.00012		0.00010	



Table 4. Performance test results with the DRIVE dataset

Cluster	Method of thresholding					
	Mean			Median		
	SEN (%)	SPE (%)	AUC (%)	SEN (%)	SPE (%)	AUC (%)
2	70.590	98.530	84.560	70.650	98.520	84.580
3	73.570	98.250	85.910	87.260	93.430	90.350
4	73.460	98.190	85.830	84.030	94.990	89.510
5	75.190	97.920	86.560	88.550	91.860	90.210
6	76.240	97.730	86.980	89.320	90.830	90.080
7	77.680	97.460	87.570	91.840	87.500	89.670
8	79.770	96.940	88.360	92.890	85.190	89.040
9	79.920	96.570	88.250	94.090	80.380	87.240
10	82.120	96.040	89.080	93.480	81.810	87.640

ble 4. Table 4 shows that the best performance of the mean thresholding method occurs when the number of clusters is 10, whereas for the median thresholding method when the number of clusters is 3. Referring to the results of 20 retinal images tested, a statistical test can be performed. Tests are carried out to compare the two mean and median thresholding methods. The results of the tests conducted are shown in Table 3. Table 3 shows that median thresholding is able to provide significantly better performance than the mean thresholding. That is because the threshold value generated from the median thresholding method is smoother so that the results of the segmentation are better.

The results of the test are shown in Tables 2 and 4, it also shows that the number of clusters for the mean thresholding method is greater than the median thresholding method. It also shows the computation time of mean thresholding is longer than the median thresholding. This is shown when testing the number of clusters 1–10, the best performance of the mean thresholding method occurs in the 10th cluster, while in the median thresholding in the number of clusters 3. It also shows the mean thresholding takes 3 times longer.

The test results when using the best number of clusters in the mean thresholding and median thresholding methods can be shown in Figures 3 and 4. Figures 3 and 4 show the image of the fundus camera, green channel and segmentation results. The number of clusters used is 8 for the mean thresholding method and 5 for the median thresholding when testing is done with the STARE dataset. The output for each process is shown in Figure 3. The output of the fundus camera is shown in Figure 3(a), green channel in Figure 3(b), segmentation by the mean thresholding method with 8 clusters is shown in Figure 3(c),

while for median thresholding with 5 cluster Figure 3(d). In testing using the DRIVE dataset, the best conditions occur in the number of clusters 10 for the mean thresholding method, and the number of clusters 3 for the median thresholding. The outputs for some of the main processes are shown in Figure 4, namely the fundus camera output in Figure 4(a), the green channel in Figure 4(b), segmentation with mean thresholding 10 the cluster in Figure 4(c), while median thresholding with 3

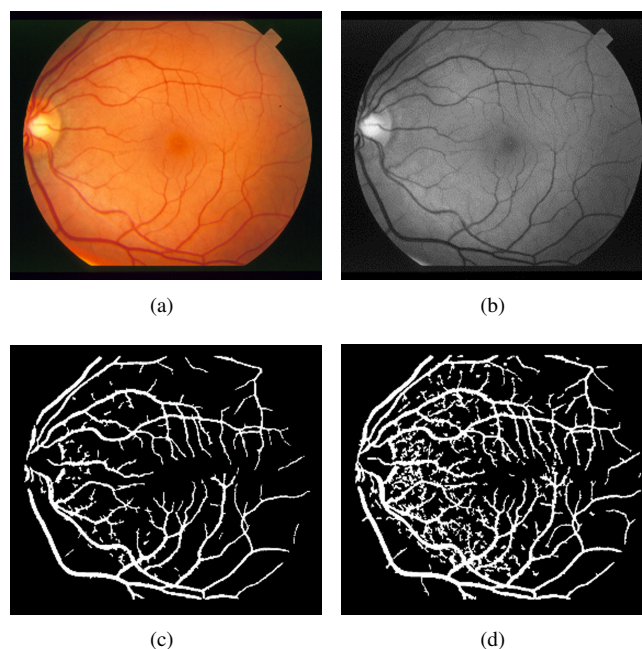
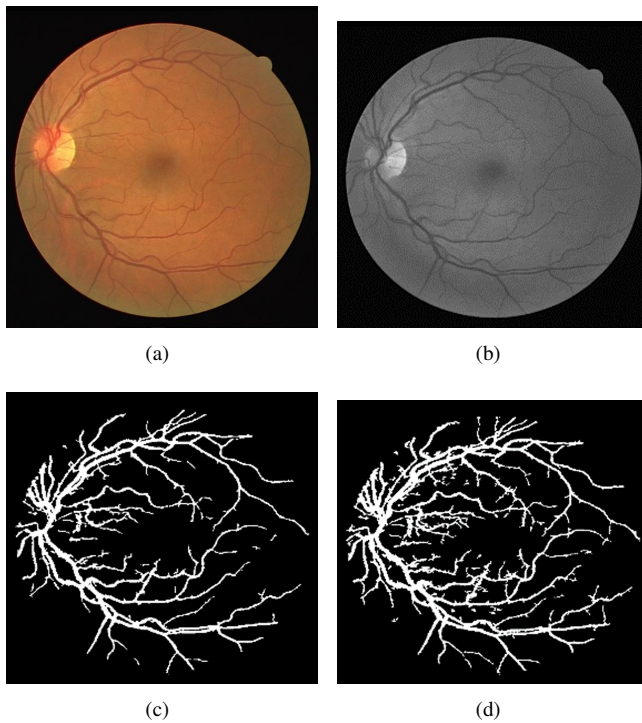


Figure 3. Output image on a hybrid segmentation system with the STARE dataset: (a) fundus image retina, (b) green channel image, (c) mean thresholding with 8 clusters, and (d) median thresholding with 5 cluster.



**Figure 4.** Output image on hybrid segmentation system with DRIVE dataset: (a) fundus image retina, (b) green channel image, (c) mean thresholding with 10 clusters, and (d) median thresholding with 3 cluster.

the cluster in Figure 4(d). The segmentation output is the final output which is then analyzed for performance, with stages as shown in Figure 1.

The segmentation model using hybrid SOM-ANN with median thresholding has advantages which are compared to a number of previous studies. Previous studies generally put more emphasis on high specificity values, so the sensitivity and specificity differences were very high. The difference between the two parameters is relatively small shown in previous studies conducted by Wiharto and Palgunadi [19] and Oloumi et al. [20]. In both studies have AUC values of 89.041% and 89.70%, with differences in sensitivity and specificity  $\leq 4.5\%$ . Both studies are still larger than the proposed model. The proposed model has a relatively small difference of 0.17%, with AUC of 90.59%. If referring to the AUC value, the proposed model is included in the very good category (AUC > 90%) [18], besides that the proposed model has a performance with balanced sensitivity and specificity parameters, so that the AUC is the same.

The proposed retinal blood vessel segmentation hybrid model has a performance with AUC values above 90%, whereas most AUC from a number of studies that have been done are still

below 90% on average. One of the improvements is caused by the ability of SOM-ANN to separate background pixels that are almost the same as blood vessels. In these conditions, the combination of SOM-ANN with the median thresholding method is still able to cluster these pixels into the background cluster. The number of such pixels is relatively large, so the errors in clustering pixels will affect segmentation performance. Examples of the ability to cluster these pixel types are low, as demonstrated by Dey et al. [4]. The study used FCM, where the performance produced with AUC only reached 77.14%. This shows that the ability of the system when there are 100 pixels of blood vessels, the system can detect 90 pixels as blood vessels, while others are translated as backgrounds. It is different with the result by Dey et al. [4], which detected blood vessels as many as 77 pixels.

In the medical world, the AUC value is in the range of 50%-100%, so good value is the AUC value to 100%. A good ability to translate blood vessel pixels is translated as blood vessel pixels, which will give good results in subsequent processes, for example, to measure the ratio of arteriovenous. If too many pixels of the blood vessels are translated as background, it will cause the arteriovenous ratio, which can be smaller or larger than the original condition. The arteriovenous ratio is a sign of hypertensive retinopathy, so this will have an impact on the outcome of a diagnosis decision. Inaccuracy in translating pixel of blood vessels can also affect in determining the retinal tortuosity of blood vessels. This can be demonstrated in research conducted by Wiharto et al. [21]. This study to find out the existence of tortuosity is done by fractal analysis, the inaccuracy in translating the blood vessels will affect the value of the fractal dimensions, which will ultimately have an impact on the incorrect results of the diagnosis.

The comparisons with several previous studies with various methods used are shown in Table 5. Comparisons were made using the DRIVE and STARE datasets. Table 5 shows that Primitivo et al. [22] has relatively the same performance as the research proposed when using the DRIVE dataset, but is lower for the STARE dataset. In this study, the segmentation model used is divided into two, namely blood vessel segmentation and optic disc removal. The method used is a combination of lateral inhibition, differential evolution, and morphology. The research conducted by Geetharamani and Balasubramanian [23], the proposed method combines a number of methods, both in the process of preprocessing and segmentation. In the preprocessing process, the Gabor filter is used to repair it, while the segmentation process uses principle component analysis,

Table 5. Comparison with a number of previous studies

Study	STARE			DRIVE		
	SEN (%)	SPE (%)	AUC (%)	SEN (%)	SPE (%)	AUC (%)
Frangi et al. [24]	-	-	-	91.370	63.370	78.370
Kar et al. [7]	-	-	-	76.450	98.090	87.270
Lupascu et al. [10]	-	-	-	69.623	97.022	83.323
Hassanien et al. [11]	64.900	98.000	81.450	72.100	97.100	84.600
Oloumi et al. [20]	-	-	-	87.600	91.800	89.700
Rezae et al. [25]	72.020	97.410	84.715	71.890	97.930	84.910
Geetharamani et al. [23]	-	-	-	70.790	97.780	84.285
Wiharto et al. [19]	90.686	80.466	85.576	91.187	86.896	89.041
Diaz et al. [22]	83.310	96.190	89.750	84.640	97.010	90.825
Nugroho et al. [26]	75.500	90.380	82.940	72.130	89.650	84.390
Sabaz et al. [27]	-	-	-	97.600	72.600	85.100
Proposed	90.500	90.670	90.590	87.260	93.430	90.350

k-means clustering, bagging classification, and image post-processing. In post-processing, it connects between component analysis and morphology. The performance of this study is very good on the specificity parameters, but the sensitivity is relatively low, so the AUC value is below 90%. Referring to research conducted by Budayan et al. [3] confirmed that the ability of the SOM-ANN algorithm have a better ability than k-means so that the performance for the AUC parameters in the proposed research is better than that of Geetharamani and Balasubramanian [23].

Previous studies using SOM-ANN were conducted by Lupascu and Tegolo [10]. This study using a combination of SOM-ANN with k-means. The SOM-ANN algorithm is used to group parts of the same image, to be further divided into two parts with the k-means algorithm. This combination is able to provide performance with AUC 83.323% parameters. The performance is still relatively lower compared to the proposed hybrid model. If seen from the method used in the research of Lupascu and Tegolo [10], it certainly requires a longer computational time compared to the proposed model. This is caused by the use of two clustering algorithms. The length of computation time required in the study is not proportional to the resulting performance.

## 4. Conclusion

The hybrid segmentation model using SOM-ANN and median thresholding can provide good performance. This is evidenced

by the presence of AUC parameters 90.350% for DRIVES and 90.590% for STARE. The proposed model also has a relatively better performance compared to a number of recent studies. The use of the median thresholding method from the cluster center is effective because the best performance occurs in the small number of cluster centers so that it can reduce the computing time of SOM-ANN which takes a relatively long time. Further research is to calculate the value of the arteriovenous ratio based on segmented blood vessels and can also be continued for the diagnosis of hypertension retinopathy.

## Conflict of Interest

No potential conflict of interest relevant to this article was reported.

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## References

- [1] C. Anderson, T. Henner, and J. Burkey, "Tablet computers in support of rural and frontier clinical practice," *International Journal of Medical Informatics*, vol. 82, no. 11, pp.



- 1046-1058, 2013. <https://doi.org/10.1016/j.ijmedinf.2013.08.006>
- [2] M. Hegland, "Data mining: challenges, models, methods and algorithms," 2003, Available <http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.4.4513>
- [3] C. Budayan, I. Dikmen, and M. T. Birgonul, "Comparing the performance of traditional cluster analysis, self-organizing maps and fuzzy C-means method for strategic grouping," *Expert Systems with Applications*, vol. 36, no. 9, pp. 11772-11781, 2009. <https://doi.org/10.1016/j.eswa.2009.04.022>
- [4] N. Dey, A. B. Roy, M. Pal, and A. Das, "FCM based blood vessel segmentation method for retinal images," *International Journal of Computer Science and Network*, vol. 1, no. 3, pp. 1-5, 2012.
- [5] S. Supot, C. Thanapong, P. Chuchart, and S. Manas, "Automatic segmentation of blood vessels in retinal image based on fuzzy k-median clustering," in *Proceedings of 2007 IEEE International Conference on Integration Technology*, Shenzhen, China, 2007, pp. 584-588. <https://doi.org/10.1109/ICITECHNOLOGY.2007.4290384>
- [6] N. Memari, A. R. Ramli, M. I. B. Saripan, S. Mashohor, and M. Moghbel, "Retinal blood vessel segmentation by using matched filtering and fuzzy c-means clustering with integrated level set method for diabetic retinopathy assessment," *Journal of Medical and Biological Engineering*, vol. 39, no. 5, pp. 713-731, 2019. <https://doi.org/10.1007/s40846-018-0454-2>
- [7] S. S. Kar and S. P. Maity, "Extraction of retinal blood vessel using curvelet transform and fuzzy c-means," in *Proceedings of the 22nd International Conference on Pattern Recognition*, Stockholm, Sweden, 2014, pp. 3392-3397. <https://doi.org/10.1109/ICPR.2014.584>
- [8] T. Mapayi, J. R. Tapamo, and S. Viriri, "Retinal vessel segmentation: a comparative study of fuzzy C-means and sum entropy information on phase congruency," *International Journal of Advanced Robotic Systems*, vol. 12, article no. 133, 2015. <https://doi.org/10.5772/60581>
- [9] G. B. Kande, T. S. Savithri, and P. V. Subbaiah, "Segmentation of vessels in fundus images using spatially weighted fuzzy c-means clustering algorithm," *International Journal of Computer Science and Network Security*, vol. 7, no. 12, pp. 102-109, 2007.
- [10] C. A. Lupascu and D. Tegolo, "Automatic unsupervised segmentation of retinal vessels using self-organizing maps and k-means clustering," in *Computational Intelligence Methods for Bioinformatics and Biostatistics*. Heidelberg: Springer, 2010, pp. 263-274. [https://doi.org/10.1007/978-3-642-21946-7\\_21](https://doi.org/10.1007/978-3-642-21946-7_21)
- [11] A. E. Hassanien, E. Emary, and H. M. Zawbaa, "Retinal blood vessel localization approach based on bee colony swarm optimization, fuzzy c-means and pattern search," *Journal of Visual Communication and Image Representation*, vol. 31, pp. 186-196, 2015. <https://doi.org/10.1016/j.jvcir.2015.06.019>
- [12] J. Staal, M. D. Abramoff, M. Niemeijer, M. A. Viergever, and B. Van Ginneken, "Ridge-based vessel segmentation in color images of the retina," *IEEE Transactions on Medical Imaging*, vol. 23, no. 4, pp. 501-509, 2004. <https://doi.org/10.1109/TMI.2004.825627>
- [13] A. D. Hoover, V. Kouznetsova, and M. Goldbaum, "Locating blood vessels in retinal images by piecewise threshold probing of a matched filter response," *IEEE Transactions on Medical Imaging*, vol. 19, no. 3, pp. 203-210, 2000. <https://doi.org/10.1109/42.845178>
- [14] J. Ma, X. Fan, S. X. Yang, X. Zhang, and X. Zhu, "Contrast limited adaptive histogram equalization-based fusion in YIQ and HSI color spaces for underwater image enhancement," *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 32, no. 7, article no. 1854018, 2018. <https://doi.org/10.1142/S0218001418540186>
- [15] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*. Upper Saddle River, NJ: Prentice-Hall, 2002.
- [16] T. Kohonen, "Essentials of the self-organizing map," *Neural Networks*, vol. 37, pp. 52-65, 2013. <https://doi.org/10.1016/j.neunet.2012.09.018>
- [17] L. Fausett, *Fundamentals of Neural Networks: Architectures, Algorithms, and Applications*. Englewood Cliffs, NJ: Prentice-Hall, 1994.
- [18] F. Gorunescu, *Data Mining: Concepts, Models and Techniques*. Berlin: Springer, 2011.

- [19] Wiharto and Y. S. Palgunadi, "Blood vessels segmentation in retinal fundus image using hybrid method of Frangi filter, Otsu thresholding and morphology," *Blood Vessels*, vol. 10, no. 6, pp. 417-422, 2019.
- [20] F. Oloumi, A. K. Dhara, R. M. Rangayyan, and S. Mukhopadhyay, "Detection of blood vessels in retinal fundus images," *Computer Science Journal of Moldova*, vol. 22, no. 2, pp. 155-185, 2014.
- [21] Wiharto, E. Suryani, and M. Y. Kipti, "Assessment of early hypertensive retinopathy using fractal analysis of retinal fundus image," *TELKOMNIKA*, vol. 16, no. 1, pp. 445-454, 2018. <http://doi.org/10.12928/TELKOMNIKA.v16i1.6188>
- [22] D. Primitivo, R. Alma, C. Erik, V. Arturo, C. Edgar, P. C. Marco, and Z. Daniel, "A hybrid method for blood vessel segmentation in images," *Biocybernetics and Biomedical Engineering*, vol. 39, no. 3, pp. 814-824, 2019. <https://doi.org/10.1016/j.bbe.2019.06.009>
- [23] R. GeethaRamani and L. Balasubramanian, "Retinal blood vessel segmentation employing image processing and data mining techniques for computerized retinal image analysis," *Biocybernetics and Biomedical Engineering*, vol. 36, no. 1, pp. 102-118, 2016. <https://doi.org/10.1016/j.bbe.2015.06.004>
- [24] A. F. Frangi, W. J. Niessen, K. L. Vincken, and M. A. Viergever, "Multiscale vessel enhancement filtering," In *Medical Image Computing and Computer-Assisted Intervention*. Heidelberg, Springer: 1998, pp. 130-137.
- [25] K. Rezaee, J. Haddadnia, and A. Tashk, "Optimized clinical segmentation of retinal blood vessels by using combination of adaptive filtering, fuzzy entropy and skeletonization," *Applied Soft Computing*, vol. 52, pp. 937-951, 2017. <https://doi.org/10.1016/j.asoc.2016.09.033>
- [26] H. A. Nugroho, R. A. Aras, T. Lestari, and I. Ardiyanto, "Retinal vessel segmentation based on Frangi filter and morphological reconstruction," in *Proceedings of 2017 International Conference on Control, Electronics, Renewable Energy and Communications (ICCREC)*, Yogyakarta, Indonesia, 2017, pp. 181-184. <https://doi.org/10.1109/ICCEREC.2017.8226686>
- [27] F. Sabaz and U. Atila, "ROI detection and vessel segmentation in retinal image," *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. 42, no. 4/W6, pp. 85-89, 2017. <https://doi.org/10.5194/isprs-archives-XLII-4-W6-85-2017>



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