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A Fundus Retinal Vessels Segmentation Scheme Based on the Improved Deep Learning U-Net Model

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ABSTRACT Retinal vascular segmentation is very important for diagnosing fundus diseases. However, the existing methods of retinal vascular segmentation have some problems, such as low microvascular segmentation and wrong segmentation of pathological information. To solve these problems, we developed a fundus retinal vessels segmentation based on the improved deep learning U-Net model. First, enhance the retinal images. Second, add the residual module in the process of designing the network structure, which solved the problem of the traditional deep learning U-Net model is not deep enough. By using the improved deep learning U-Net model, it can connect the output of the convolutional layer with the output of the deconvolution layer to avoid low-level information sharing, and solved the problem of performance degradation of deep convolutional neural networks in residual networks under extreme depth conditions. By verifying on the DRIVE (digital retinal images for vessel extraction) dataset, the segmentation accuracy, sensitivity, and specificity of the proposed method are 96.50%, 93.1%, and 98.63% respectively.

INDEX TERMS Retina, blood vessels, improved deep learning U-Net model, residual.

I. INTRODUCTION

The eye is a visual system, which is one of the most important sensory organs of human beings. More than 70% of the external information obtained by human beings comes from the visual system of the eye [1]. Fundus images contain multiple structures including the retina, and modern imaging technology can directly observe the microvascular structure of the retina through the fundus images, so as to realize the relevant research on the physiological characteristics of retinal. Retinal vascular segmentation is the basis of fundus image research. As the only deep microvessel that can be observed in human body, the retinal blood vessel of fundus can reflect the influence of diseases on retinal blood vessel network through the segmentation of its morphological structure. However, due to the contrast between retinal target blood vessels and the background, the uneven changes in the width and curvature of blood vessels, and the influence of noise during the acquisition of retinal images, retinal blood vessel segmentation faces great challenges. The analysis of retinal blood vessels in the base is a valuable tool for disease analysis.

In the diagnosis of retinal fundus images, the condition and appearance of the vascular network can be considered an important aspect. At the present stage, unsupervised and supervised retinal image segmentation methods rely heavily on standard features of artificial or expert markers to characterize differences between blood vessels and backgrounds. However, the difficulty is how to make the algorithm adaptive to the vascular scale, shape and geometry transformation, achieve intelligent identification of vascular features, so as to accurately and effectively segment the effective target contour structure, thus achieve the demand of auxiliary clinical diagnosis.

Our article organization structure is: the first part is the introduction. This part mainly introduces the importance of retinal blood vessel in clinical diagnosis and the significance of retinal blood vessel segmentation. The second part is related work. This section mainly introduces the domestic and foreign research on retinal vascular segmentation, and then briefly introduces the method we proposed. The third part mainly introduces our method in detail. Including image

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preprocessing, image enhancement, network structure and so on. The fourth part is the experiment and discussion section, which introduces the way of our evaluation and the results of our experiment. The fifth part is the conclusion, which summarizes the methods we put forward.

II. RELATED WORKS

For retinal blood vessel segmentation, it included unsupervised and supervised segmentation. Unsupervised learning methods typically use a filter response or other model-based technique to extract blood vessels. According to different image processing methods, it can be subdivided into three categories: matched filter, vessel tracking and model-based methods. Matching filter used two-dimensional convolution kernel to convolve with fundus image and the response of the matched filter indicates the existence of blood vessel. Chaudhuri *et al.* [2] combines the matched filtering model with the ant colony algorithm, and performs both treatments on the fundus image simultaneously, and then combines the two to obtain the final vascular network. Jiang and Mojon [3] uses adaptive local threshold segmentation to segment the blood vessels, and finds the threshold for each pixel in the neighborhood window instead of thresholding the entire image. Gang *et al.* [4] proposed a two-dimensional gaussian filtering method with amplitude correction through experimental simulation and mathematical analysis. Zhang et al.[5] proposed a matching filtering method called mf-fdog to detect vascular edges. Vlachos and Dermatas [6] proposed a new retinal image vascular network extraction algorithm using the iterative line tracking program. This method can calculate the exact vascular width, but it is often unable to detect vessels without seed points. The model-based method uses explicit vascular models, such as vascular contour model and the deformation model, to extract fundus vessels. Zana and Klein [7] proposed an algorithm based on mathematical morphology and curvature estimation to detect blood vessels. Espona *et al.* [8] used the classic serpentine model to segment retinal blood vessels, and introduced morphological operations to improve them.

Although many scholars have developed a number of the retinal blood vessel image segmentation algorithms based on unsupervised learning, the segmentation results on micro-vessels and low-contrast images are still to be further improved. The supervised learning method is relatively simple, and the gold standard of expert segmentation is used to supervise the feasibility of the method. Compared to the unsupervised learning method, the supervised learning method is more efficient, but the drawback is that the gold standard comes from the manual segmentation of experts. Subjective and expensive.

With the re-semantic segmentation of deep learning, good results have been achieved. Many scholars have applied deep learning theory to retinal blood vessel segmentation. The retinal image segmentation algorithm based on deep learning is different from the dependence of traditional machine learning algorithms on the prior information of image data and has strong data representation ability. Wu *et al.* [9]] combines the residual network structure with the densely connected network (DenseNet) to effectively reuse the vascular features, which helps the model to learn more robust morphological structure information according to the gold standard image, but excessively The use of the Dense Block structure results in high memory usage and large computational complexity. Fu *et al.* [10] transformed the vascular segmentation problem into a boundary detection problem, identified the features using a fully-connected CNN and generated a vessel probability map, and then generated a dense global pixel correlation through the Fully Connected Conditional Random Fields (CRF). The value of the blood vessel image, but the convolutional neural network utilized by the algorithm has the characteristics of the solidification of the model geometry. The convolution unit performs the sampling of the feature information at the fixed position of the image, and cannot effectively convert according to the shape information of the blood vessel, and the conditional random field can The predictive features are refined by local and remote dependencies, but the complex shape properties associated with curvature in the blood vessels cannot be captured, resulting in incomplete microvascular segmentation. Ming *et al.* [11] combined Dense Net and u-net network to segment fundus retinal vessels, and the accuracy, sensitivity and specificity reached 96.74%, 81.50 and 98.20%, respectively. Gao *et al.* [12] combines U-net and multi-scale filtering vascular algorithm, combines artificial features with gold standard features, and uses U-net architecture to connect the coding layer with the output of the decoding layer to better solve low-level information sharing. The problem is that the segmented micro-vessels are more robust, but the geometric transformation modeling capability of the model still comes from artificial feature and data expansion, and the upsampling layer of the decoding part cannot effectively recover the details of the coding loss. Liang *et al.* [13] embedded the Dilated convolution and dense network into the u-shaped network, which not only solved the problem that the traditional network pooling layer ignored some important information, but also improved the network structure and solved the shortcomings of improper microvascular treatment in some methods, but does not have adaptive vascular scale information. The ability still has problems such as a small amount of microvascular fragmentation at the end of the optic disc and the end of the main blood vessel. Alom *et al.* [14] using U-Net to realize the segmentation process of medical images, including the segmentation of retinal blood vessels, the results show that the method is superior in segmentation. Caused by the deep residual learning [15] and U-Net [16], we developed a U-net network structure based on residual learning to solve the problem of retinal vascular segmentation. We introduced residual learning unit into U-net network to solve the problem that the more convolution operation there is, the deeper the network will be, and the network performance will decline. The effect of semantic segmentation on U-net network has been favored by many scholars. We combine the two,

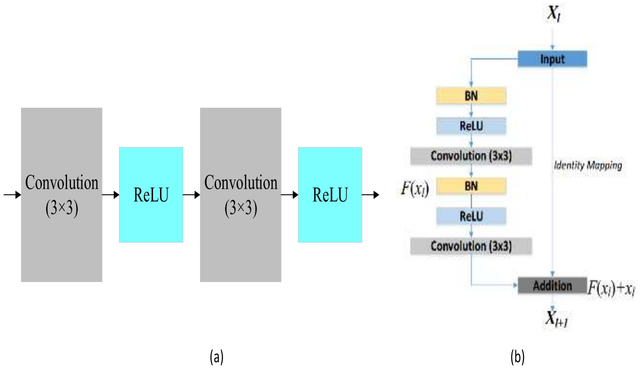


FIGURE 1. **The proposed residual learning module. (a) The structure used by traditional semantic segmentation networks and (b) our proposed improved network learning module with residuals.**

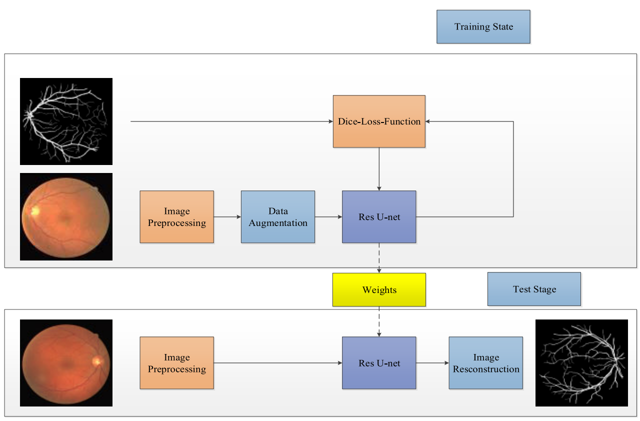


FIGURE 2. **Overview of the proposed method.**

can better play their advantages, improve the segmentation accuracy.

III. DEVELOPED METHOD

In this work, we developed a retinal vascular segmentation framework combining residual module and U-net network. The framework, presented in Fig. 2, is divided into two phases: training and testing.

In the process of training, gray level transformation, the original data and then in order to improve the adaptation of network performance, normalization of image processing, using our proposed Res U-net as the network training model, using an adaptive Nesterov Moment Estimator (Nadam) based on binary_cross-sentropy loss function is optimized, by constantly training iterations, weights to obtain the best model parameters.

After the training, the test set was tested, and the same pre-processing strategy was adopted to obtain segmentation results through the training model.

A. IMAGE PREPROCESSING

Due to the uneven illumination and vascular center line reflection in the collected retinal images, the contrast between micro vessels and background is low, and the universality of the algorithm is low, Ming *et al.* [11] to preprocessed

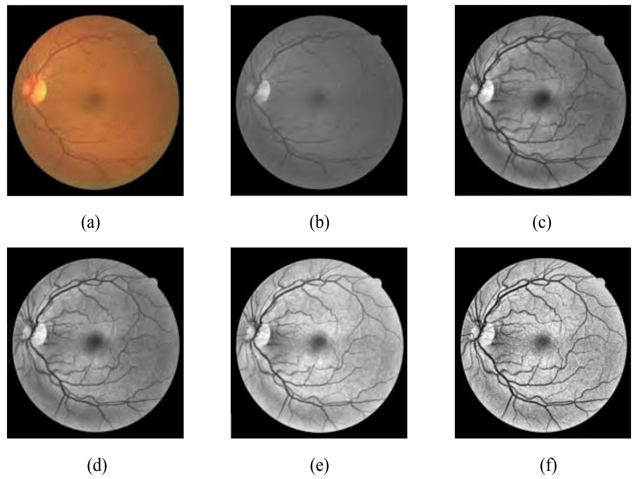


FIGURE 3. **Preprocessing results for each stage. (a) Original image. (b) Green channel. (c) CLAHE image. (d) Filter image. (e) Gamma image. (f) Multiscale morphological images.**

the collected images and obtained better data for further processing. The specific steps are as follows:

a) The green channel with high contrast between blood vessels and background in the color fundus image is extracted and denoised by bilateral filtering.
b) Limited contrast histogram equalization (CLAHE) is adopted for the green channel image after filtering and denoising. The contrast between the blood vessel and background is improved while noise is suppressed. Then, global sharpening is carried out through filter filtering to suppress the noise influence of the image enhanced by CLAHE, such as artifact and macula, so as to highlight blood vessel information.
c) Local adaptive Gamma correction [17] is used to conduct Gamma matching according to different pixel features of blood vessels and background, so as to correct the retinal image in different regions, so as to suppress the uneven light factor and the reflection of the center line.
d) Images corrected by adaptive Gamma correction were further enhanced by multi-scale morphological top-hot transformation [18]. Four scales were selected to control the control factor of image edge gradient information, adjust the difference of pixel scales of adjacent blood vessels, red uce the interference of features such as focus and the optic disc, and extract multi-scale bright and dark detail features of tiny blood vessels. The model is defined as follows:

$$f_T = I_r + k \times \sum_{i}^{n} w_i(Dop_i - Dcl_i) \tag{1}$$

where, k is retinal vascular image detail enhancement factor; I_r is the input image; f_T is the output image; Dop_i and Dcl_i are the bright details and dark details of retinal images respectively. The pre-processing results are shown in Fig. 3.

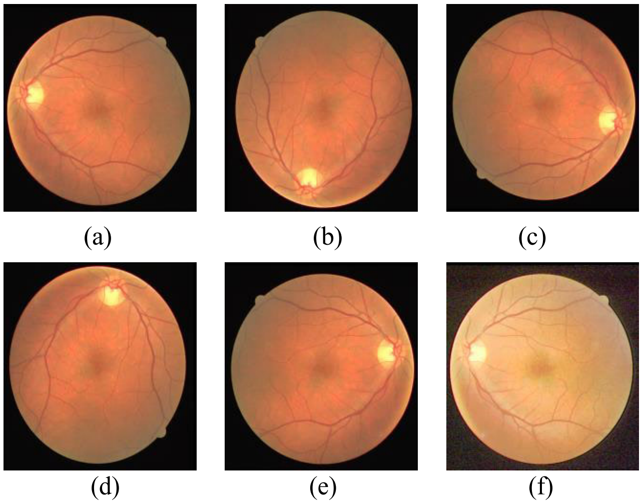


FIGURE 4. The first set of Augmentation image. (a) Original image. (b) Rotating 90° image. (c) Rotating 180° image. (d) Rotating 270° image. (e) Flip image. (f) Histogram equalization image.

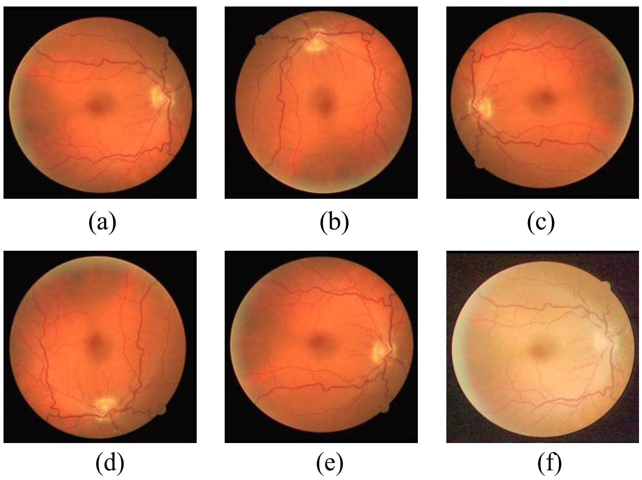


FIGURE 5. The second set of Augmentation image. (a) Original image. (b) Rotating 90° image. (c) Rotating 180° image. (d) Rotating 270° image. (e) Flip image. (f) Histogram equalization image.

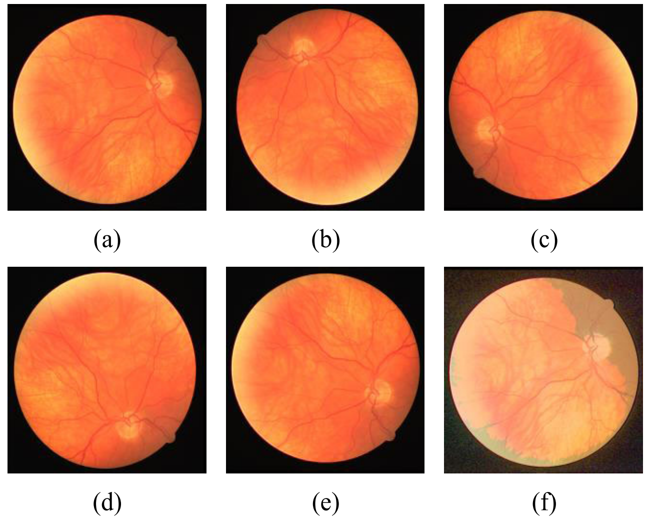


FIGURE 6. The third set of Augmentation image. (a) Original image. (b) Rotating 90° image. (c) Rotating 180° image. (d) Rotating 270° Image. (e) Flip image. (f) Histogram equalization image.

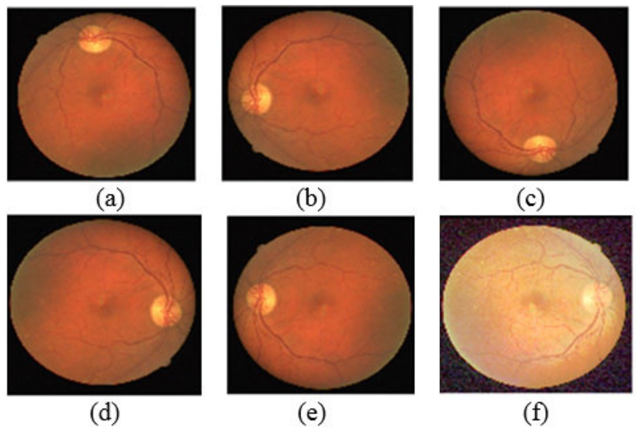


FIGURE 7. The fourth set of Augmentation image. (a) Original image. (b) Rotating 90° image. (c) Rotating 180° image. (d) Rotating 270° image. (e) Flip image. (f) Histogram equalization image.

B. IMAGE AUGMENTATION

Since the use of deep learning theory requires a large amount of data, the convolutional neural network has a certain degree of invariance to geometric transformation, deformation and illumination. We augment the dataset by processing the data by rotating 90°, 180°, 270°, and flipping.

Because there exist certain differences between the internal data, data sets some retinal vascular lesions, have taken place in some differences in image contrast, in order to increase data does not affect the final segmentation result, we selected seven groups including lesions, and normal contrast differences of data. They were randomly selected from the extended training set for analysis. Figs. 4-10 are a selection of 7 groups of enhanced images.

In the original image of Fig. 4, there are many small blood vessels. In the process of segmentation, it is inevitable that some blood vessels are not correctly segmented. By enhancing the image, the contour of the small blood vessels becomes more obvious, and the segmentation accuracy can be improved.

In Fig. 5, the background of the original image is similar to the color of the blood vessel, which hinders the learning of the characteristics of the whole blood vessel, and the original image is subjected to image enhancement processing, and both of them are used as training images, so that the characteristics of the blood vessel can be better learned.

In the original image of Fig. 6, since the texture in the retina of the fundus is large, the division of the blood vessel forms a large noise, and by the image enhancement processing, the texture of the blood vessel becomes clearer, which contributes to the segmentation of the blood vessel.

The original image in Fig. 7 is dark due to the influence of the collection environment, and only the thicker main blood vessels can be seen. This poses a great challenge to the segmentation of small blood vessels. The image enhancement

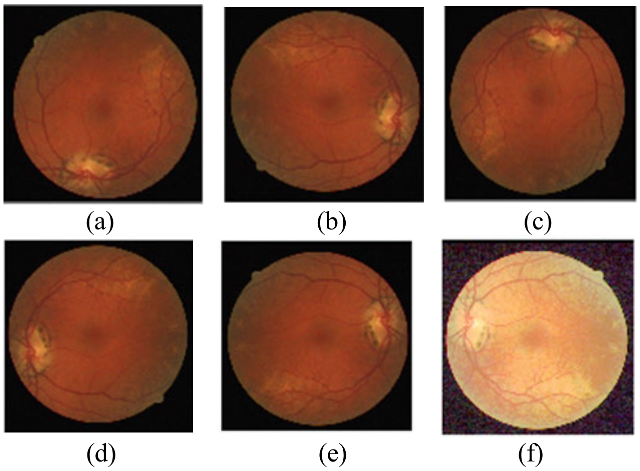


FIGURE 8. The fifth set of Augmentation image. (a) Original image. (b) Rotating 90° image. (c) Rotating 180° image. (d) Rotating 270° image. (e) Flip image. (f) Histogram equalization image.

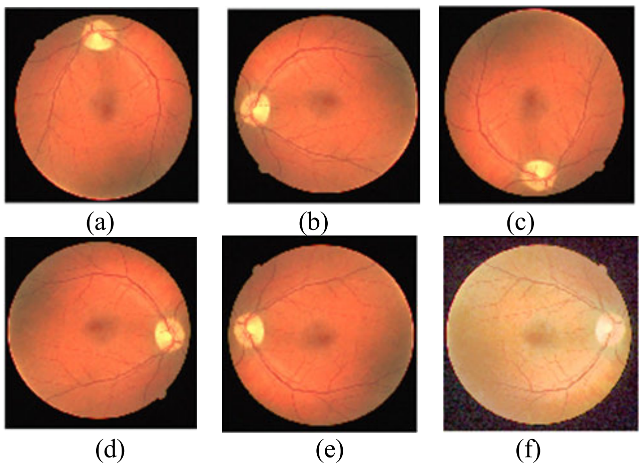


FIGURE 9. The sixth set of Augmentation image. (a) Original image. (b) Rotating 90° image. (c) Rotating 180° image. (d) Rotating 270° image. (e) Flip image. (f) Histogram equalization image.

process makes the main blood vessels more obvious. At the same time, it shows more details of small blood vessels.

In the original image of Fig. 8, the background color is similar to that of the blood vessel. In the process of segmentation, segmentation errors are inevitable. After the image enhancement process, the difference between the background and the blood vessel is increased, making the blood vessel more obvious.

In the original image of Fig. 9, the retina blood vessels of the fundus are obscured by the shadow portion, and the contrast between the shadow portion and the blood vessel is increased by enhancing the image processing, and more blood vessel characteristics can be learned during the segmentation process.

In Fig. 10, images are different from other data sets, shows the same histogram equalization status. Through processing, the data set can be expanded without changing the texture and other information of the original data set, which can be used as real data.

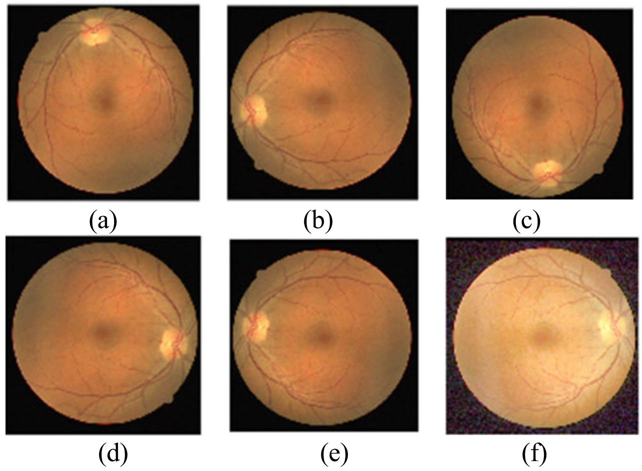


FIGURE 10. The seventh set of Augmentation image. (a) Original image. (b) Rotating 90° image. (c) Rotating 180° image. (d) Rotating 270° image. (e) Flip image. (f) Histogram equalization image.

In these 7 sets of data sets, rotation and rotation did not change the shape and texture information of retinal blood vessels, but only changed the direction, which is the special feature of convolutional neural network. It is less sensitive to these changes and can be used as a training set. For histogram equalization, it is the pixel value of the data set that changes, but it does not change the direction of blood vessels, and micro-vessels are not ignored.

C. RESUNET ARCHITECTURE

1) U-NET

In the field of semantic segmentation, in order to achieve the best segmentation effect, it is very important for many scholars to retain some details while retaining most areas of interest [16] and [19]. However, training a as the depth of the semantic segmentation study network is very difficult, on the one hand is the size of the amount of data, on the other hand while using the trained model test, very little time consuming, but training such a perfect network is very difficult, based on this, scholars have done training using a network is put forward, based on the selected data network of fine-tuning, it is often said that the migration study [16]. Another method is to enhance the acquired data. Since convolutional neural network is less sensitive to geometric deformation, some scholars will expand the data set according to this feature [19]. In addition to the above solutions, it is possible to change the network structure to solve the above problems. The network can not only consider the global information, but also effectively optimize the detailed information. In our method, the combination of residual element and U-net network can improve the segmentation performance of the network more effectively.

2) RESIDUAL UNIT

In recent years, research has found that the depth of the network is a key factor to optimize network performance. However, as the depth of the network deepens, the gradient

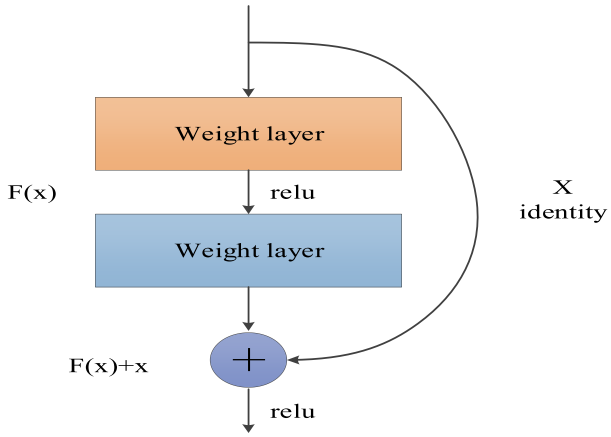


FIGURE 11. **Residual learning: A building block.**

disappearance & explosion problem is very obvious, and the network even degenerates. This degradation problem is solved with the help of a deep residual learning model. It does not expect each layer to directly match a mapping, but explicitly let these layers fit the residual mapping. The residual module is shown in Fig. 11.

Suppose the input of a certain neural network is x, the expected output is $H(x)$, if we pass the input x directly to the output as the initial result, then the goal we need to learn at this time is $F(x) = H(x) - x$. As shown in the figure, this is a ResNet Residual Unit. The Residual block is implemented by the shortcut connection. The input and output of the block are added by element-wise by the shortcut. This simple addition is not It will add extra parameters and calculations to the network, but it can greatly increase the training speed of the model and improve the training effect. When the number of layers in the model is deepened, this simple structure can solve the degradation problem well.

Just like the traditional deep learning network, batch normalization (BN), Rectified Linear Unit (ReLU) and convolution layer will be combined effectively, and the residual learning module will be combined continuously to find the best effect. To solve this problem, He *et al.* [15] conducted experiments of different combinations of the three, and proposed the network structure shown in FIG. 1. In our proposed network structure, this module is added to our deep residual U-Net network.

3) DEEP RESUNET

We develop a new network structure that combines the residual module with the u-net network to give full play to their advantages. The performance of the network is mainly reflected in two aspects: 1) the residual module can improve the performance of network training and reduce the problem of gradient descent; 2) the hopping connection of the residual module can ensure the non-degradation of information, so that we can design a deeper network structure and improve the performance of semantic segmentation as much as possible.

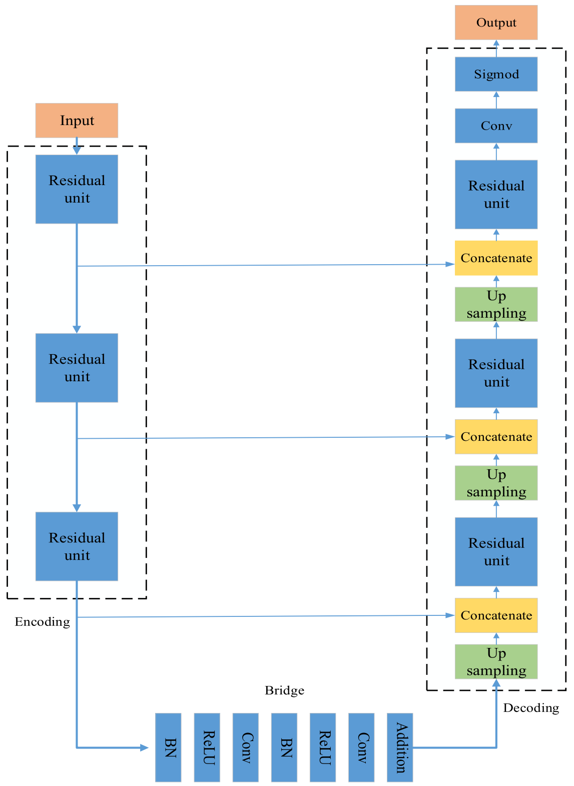


FIGURE 12. **The architecture of the developed deep ResUnet.**

Our network framework structure is shown in Fig.12. We combined the U-Net with the residual unit. The network is divided into encoding and decoding. These two parts improved the original U-Net and combined the residual unit. The network designs three residual units in the coding part, and correspondingly designs three residuals in the decoding part. The network we designed is mainly divided into three parts: the coding part, the bridging part and the decoding part. The first part is mainly feature extraction, in which a large number of features of images are extracted by convolution operation. The third part is to reconstruct the extracted features and classify them by pixel category, namely semantic segmentation. The second part is the bridge connecting decoding and coding. What's more important is that in these three parts, there are residual modules, residual modules are composed of two convolution kernel of 3 by 3 and an identity map.

4) LOSS FUNCTION

In the process of network training, we take binary cross entropy as a loss function, and the network output of the last layer is $O_i \in [0, 1]$, and let $y_i \in \{0, 1\}$ be real segmentation result. We designed the loss function as follows:

$$L_{bce} = \sum_i y_i \log o_i + (1 - y_i) \log(1 - o_i) \tag{2}$$

In order to improve the performance of network training more effectively, we choose Nesterov Adaptive Moment

Estimation (Nadam) to train network structure. Other derivatives may also improve our network training performance.

Nadam is similar to Adaptive Moment Estimation (Adam) with a Nesterov momentum term. Nadam has a stronger constraint on learning rate and a more direct influence on the update of gradient. Generally speaking, Nadam can be used for better effect in places that want to use root mean square prop (RMSprop) or Adam of driving quantity. In order to achieve the best segmentation effect, we choose to use Nadam to train the network structure.

IV. EXPERIMENTS AND DISCUSSIONS

The simulation platform of the experiment is PyCharm, using keras and TensorFlow port, the computer is configured as Inter(R) Core(TM) i7-8750H @2.20GHz, 16GB memory, Nvidia GeForce GTX 1070 GPU, using 64 bit Win10.

A. DATASET

The dataset is from DRIVE (digital retinal images for vessel extraction). The dataset was composed by Nieneijer team in 2004 [20]. Including 20 training images and 20 test images, and image pixels is 565×584. Each image corresponds to the manual segmentation results of two ground truth.

We all know that deep learning requires a large number of samples for training and learning, so we expand the data set, and the specific expansion has been introduced in the third part. In the end, 1000 data sets participated in the training and 200 were tested, to further reduce the over-fitting phenomenon during the training process.

B. EVALUATION METRICS

In order to systematically quantitatively analyze the performance of the segmentation results of the proposed algorithm, we use three indicators as the metrics:

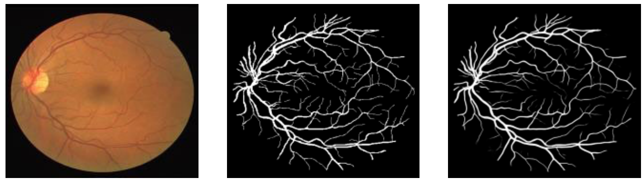
$$Sensitivity = \frac{TP}{TP + FN} \tag{3}$$

$$Specificity = \frac{TN}{TN + FP} \tag{4}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

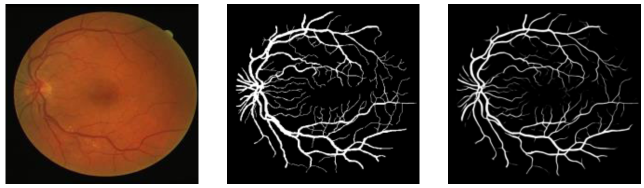
where T_p, T_N, F_P, F_N are true positive, true negative, false positive, false negative, respectively. Sensitivity, also known as true positive rate, indicates the percentage of correctly classified vascular pixels to true vascular pixels; specificity indicates the percentage of correctly classified non-vascular pixels to true non-vascular pixels; accuracy indicates correct Classification of blood vessels to drink non-vascular pixels as a percentage of the total pixels of the entire image.

The ROC (receiver operating characteristic) curve is an important criterion for measuring the comprehensive performance of blood vessel segmentation results. The horizontal axis is the false positive rate (FPR) and the vertical axis is true positive rate (TPR). The trend of the two under different thresholds, the larger the value, the better the robustness of the segmentation performance of the algorithm.



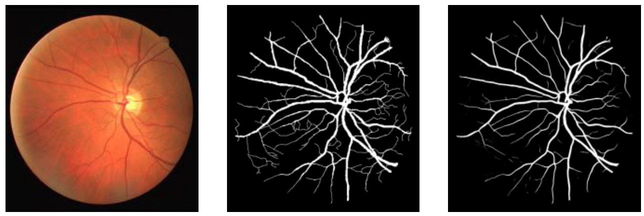
(a) (b) (c)

FIGURE 13. **The first set of segmentation results. (a) Original image. (b) Ground truth. (c) Propose method.**



(a) (b) (c)

FIGURE 14. **The second set of segmentation results. (a) Original image. (b) Ground truth. (c) Propose method.**



(a) (b) (c)

FIGURE 15. **The third set of segmentation results. (a) Original image. (b) Ground truth. (c) Propose method.**

(a) (b) (c)

FIGURE 16. **The fourth set of segmentation results. (a) Original image. (b) Ground truth. (c) Propose method.**

C. SUBJECTIVE EVALUATION

Figs. 13-19 show different results of the algorithm in this paper. These results are described in detail below

Intuitively, the segmentation of Fig. 13 is relatively accurate, as it is the segmentation of some tiny blood vessels.

The segmentation of Fig. 14 is relatively accurate, but the smiling blood vessels inside the eyeball are neglected.

The segmentation of Fig.15 was relatively accurate, and the direction of blood vessels was clear and accurate.

In Fig. 16, there are many small blood vessels at the end of the fundus retinal blood vessels, but in the results, only the main blood vessels and the thicker blood vessels are segmented, and the small blood vessels at the end are not divided, and we will be in future research work. Continue to improve the method.

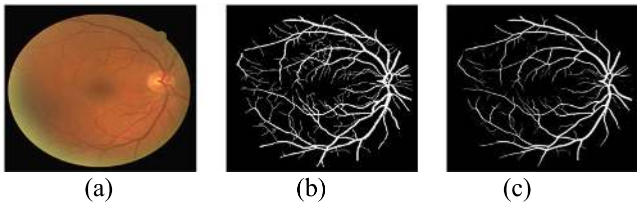


FIGURE 17. The fifth set of segmentation results. (a) Original image. (b) Ground truth. (c) Propose method.

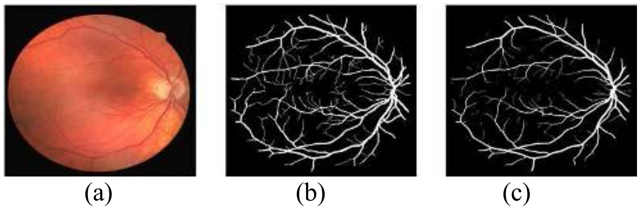


FIGURE 18. The sixth set of segmentation results. (a) Original image. (b) Ground truth. (c) Propose method.

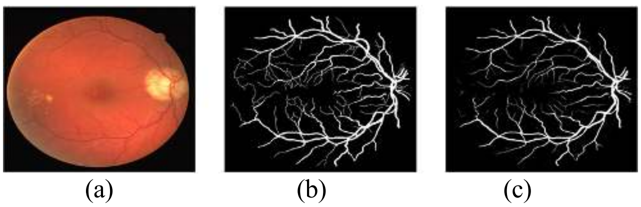


FIGURE 19. The seventh set of segmentation results. (a) Original image. (b) Ground truth. (c) Propose method.

It can be seen from the segmentation results in Fig. 17 that most of the blood vessels in the fundus retina are accurately segmented, and some small blood vessels marked in ground truth are also accurately segmented, indicating that the proposed method has high applicability to blood vessel segmentation.

The segmentation result image of Fig. 18 is compared with ground truth. At the top of the blood vessel, a blood vessel not marked in ground truth is accurately segmented, indicating that the proposed method has higher segmentation accuracy for retinal blood vessel segmentation of the fundus.

In Fig. 19, the segmentation is relatively accurate, and the tiny blood vessels are visible, which is helpful for the diagnosis of diseases, indicating the effectiveness of the algorithm.

In order to prove the feasibility of the proposed method, these results are compared with ground truth and literature segmentation results. As shown in the Fig. 20, four images are extracted from the test set randomly, (a) is the original one, (b) is the ground truth, (c) is the result of segmentation in [11], and (d) is the result of segmentation of the proposed algorithm. Subjectively, the proposed algorithm can obtain excellent segmentation effect in normal retinal vessels or lesion retinal vessels, and can segment more micro-vessels, which can segment more detailed information and better restore the blood vessel results of retinal images.

To more intuitively show the advantages of the algorithm in this paper, the ROC curve graph shown in Fig.21 is presented. It can be seen from the ROC curve that the overall

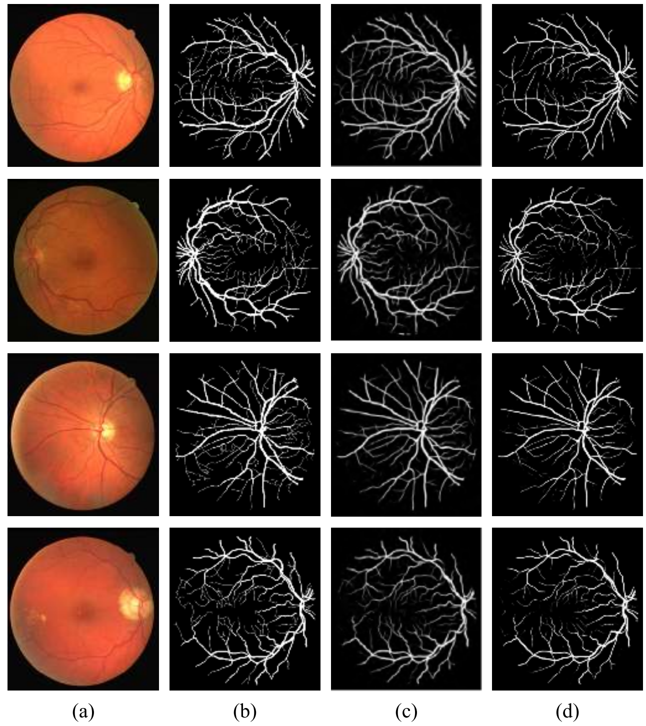


FIGURE 20. Comparisons of segmentation results on the DRIVE database. (a) Original image. (b) Ground truth. (c) Liang *et al.* [11]. (d) Propose method.

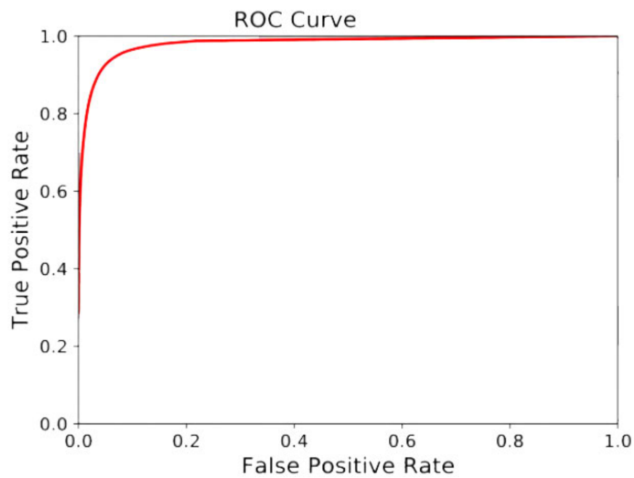


FIGURE 21. ROC chart of DRIVE dataset.

performance of the algorithm in this paper is superior, with a low false positive rate and a high true positive rate, and there may be a small error segmentation of blood vessels.

D. COMPARISONS

Furthermore, to prove the feasibility of the proposed method, the sensitivity, specificity, and accuracy of the proposed method are compared with other methods. The results as shown in Table 1. It can be shown that the proposed algorithm has better comprehensive segmentation performance.

In addition, to more intuitively present the advantages of the proposed method, the compared results are drawn

TABLE 1. Comparison of performance data between different documents.

Method	Acc	Sen	Spe	Auc
Liang et al.[13]	0.9674	0.8150	0.9820	0.9808
Alom et al.[14]	0.9531	0.7537	0.9820	-
Zhou et al.[21]	0.9469	0.8078	0.9674	-
Gao et al.[12]	0.9636	0.7802	0.9876	0.9772
Strisciuglio etal.[22]	0.9467	0.7731	0.9724	0.9588
Propose method	0.9650	0.8310	0.9863	0.9811

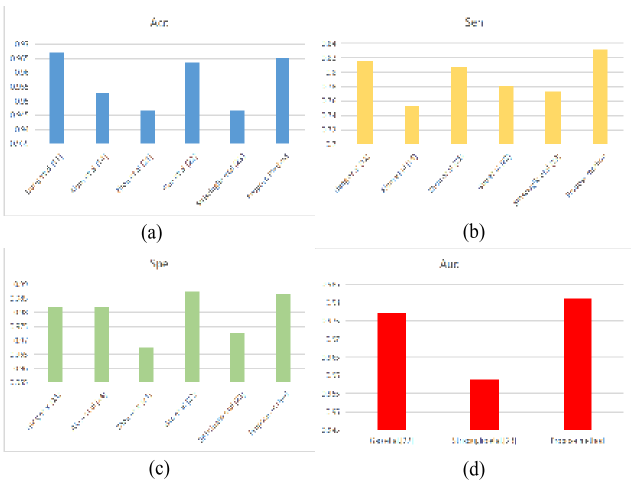


FIGURE 22. Result of experimental contrast. (a) Acc. (b) Sen. (c) Spe. (d) AUC.

in Fig. 22. It can be seen from the Fig. 22 that the overall performance of the proposed method is superior, the false positive rate is lower, the true positive rate is higher, and the possibility of mis-segmentation is smaller, which can help the clinical diagnosis.

As shown in Fig. 22, from accuracy(ACC), sensitivity(Sen), specificity(Spe) and Area Under Curve(AUC) contrast figure, while this Liang *et al.* [13] algorithm accuracy is slightly lower than literature, but comprehensive index is more outstanding, Liang *et al.* [13] in the remaining three indicators are lower than that of the proposed algorithm, the rest of the four methods is lower than the algorithm, so in this paper, the proposed algorithm can assist doctors to eye disease diagnosis, for clinical trials to lay a solid foundation for the further.

V. CONCLUSION

Accurate segmentation of retinal blood vessels in the fundus has great practical significance for helping doctors diagnose the fundus diseases. In view of the problems of insufficient resection of micro-vessels and serious mis-segmentation in traditional retinal segmentation, we proposed ResUnet which combining the U-Net with the residual learning strategy. The proposed algorithm reduced network complexity and improved segmentation accuracy. The introduction of residual element will help deepen the network depth and improve the performance of the network. The proposed algorithm is more advantageous than other methods through verification analysis on the DRIVE dataset. In future, we will continuously develop this algorithm, and apply it to more medical fields.

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