CHANNEL ATTENTION RESIDUAL U-NET FOR RETINAL VESSEL SEGMENTATION

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ABSTRACT

Retinal vessel segmentation is a vital step for the diagnosis of many early eye-related diseases. In this work, we propose a new deep learning model, namely Channel Attention Residual U-Net (CAR-U-Net), to accurately segment retinal vascular and non-vascular pixels. In this model, the channel attention mechanism was introduced into Residual Block and a Channel Attention Residual Block (CARB) was proposed to enhance the discriminative ability of the network by considering the interdependence between the feature channels. Moreover, to prevent the convolutional networks from overfitting, a Structured Dropout Residual Block (SDRB) was proposed, consisting of pre-activated residual block and DropBlock. The results show that our proposed CAR-U-Net has reached the state-of-the-art performance on two publicly available retinal vessel datasets: DRIVE and CHASE DB1.

Index Terms—Retinal vessel segmentation, CAR-U-Net, channel attention, DropBlock

1. INTRODUCTION

Retinal vessel segmentation is of great significance in the early diagnosis of eye-related diseases. For example, Diabetic Retinopathy (DR) is a universal retinal disease caused by elevated blood sugar, accompanied by retinal vascular swelling [1]. However, the manual annotating of retinal vessels by ophthalmologists is a slow and labor-intensive task, so researchers have devoted themselves to proposing automatic retinal vessel segmentation methods.

In the past few decades, researchers have proposed a great number of methods for automatic retinal vessel segmentation, which are generally separated into two categories. One is image processing methods, which include pre-processing, segmentation, and post-processing steps, such as Bankhead et al. [2] proposed the use of wavelet transform method to enhance the detection of vessel foreground and background. The other is machine learning-based methods, which mainly use the extracted vector features to train a classifier to classify pixels in the retina. For instance, Lupascu et al. [3] designed 41-D feature vector for every pixel to train the AdaBoost classifier to classify each pixel in the retinal image.

Recently, deep learning-based methods have been used for automatic segmentation of retinal vessel and have achieved excellent results. Fu et al. [4] improved the vessel segmentation ability by using a convolutional neural network (CNN) with a Conditional Random Field (CRF) layer and a side output layer. Zhang et al. [5] introduced an edge-based mechanism in U-Net [6] to reach an improved performance. Wu et al. [7] introduced a Multi-Scale Network Followed Network (MS-NFN) for retinal blood vessel segmentation. Although these deep learning-based methods have realized significant results, the interdependence between the feature channels was ignored. Motivated by the recent successful application of the channel attention mechanism in the area of medical image analysis [8-10], in this work, we introduce the channel attention mechanism to further improve the performance of retinal vessel segmentation.

In this study, we propose an innovative deep learning-based Channel Attention Residual U-Net (CAR-U-Net) model, which greatly improves the ability of deep neural networks to segment retinal vessels. Specifically, we have the following contributions: (1) Inspired by the excellent performance of the residual network [11] and the success of DropBlock in preventing convolutional networks from overfitting [12], we integrate DropBlock into the pre-activated residual block and propose Structured Dropout Residual Block (SDRB). We use the proposed SDRB to build a new deep U-shaped network, which is named Structured Dropout Residual U-Net (SDR-U-Net). (2) We consider the relationship between the feature channels, and add the channel attention mechanism on the basis of SDRB to propose Channel Attention Residual Block (CARB). Based on these, we propose Channel Attention Residual U-Net (CAR-U-Net). (3) We evaluate both models on the DRIVE and CHASE DB1 datasets. The results demonstrate that our proposed CAR-U-Net has reached the state-of-the-art performance on both datasets.

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2. PROPOSED METHODOLOGY

2.1. Network Architecture

The detailed architecture of Channel Attention Residual U-Net (CAR-U-Net) is displayed in Figure 1. The network structure of CAR-U-Net is derived from U-Net, where the original convolution blocks are replaced by SDRB and CARB. CAR-U-Net contains two paths with the same number of residual blocks, namely the contracting path (left) and the expansive path (right). In the contracting path, each step includes a SDRB, a CARB followed by Batch Normalization (BN), a Rectified Linear Unit (ReLU), and a 2×2 max pooling layer with step size of 2 is used for downsampling. Each step in the expansive path includes using a transposed convolution operation for upsampling, which halves the number of feature channels, concatenates with the parallel feature map from the contracting path, followed by a SDRB, a CARB, BN, and a ReLU. In the last layer, we employed 1×1 convolution and sigmoid activation function to get the required feature map.

![Fig. 1: The CAR-U-Net architecture](image)

2.2. Channel Attention (CA)

CA was first used as a squeeze and excitation block for classification [15], which generates channel attention maps by using the relationship between the channels. In order to aggregate the spatial information, we use both average pooling and maximum pooling to obtain finer channel-wise attention [16]. Formally, input feature \( F \in \mathbb{R}^{H \times W \times C} \) through the channel-wise max-pooling and average-pooling can generate \( F_{mp} \in \mathbb{R}^{1 \times 1 \times C} \) and \( F_{ap} \in \mathbb{R}^{1 \times 1 \times C} \), respectively, e.g., at the \( c \)-th channel:

\[
F_{mp}^c = \text{Max}(F^c(i,j)), 0 < c < C, 0 < i < H, 0 < j < W
\]

\[
F_{ap}^c = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} F^c(i,j), 0 < c < C
\]

where \( \text{Max}() \) obtains the maximum number, \( P^c() \) represents the pixel value at a specific position of the \( c \)-th channel, and \( H, W, \) and \( C \) stand for the height, width, and the number of channels of the input feature \( F \), respectively. The two descriptors are then forwarded to a shared weight network consisting of Multi-Layer Perceptron (MLP) with a single hidden layer to generate a channel attention map \( M^c \in \mathbb{R}^{1 \times 1 \times C} \). CA sets the hidden activation size to \( R^{1 \times 1 \times C}/r \), where \( r \) is the reduction rate, which reduces the parameter overhead, and we set the value of \( r \) to 16. Then, CA applies the element-wise addition to combine the output feature vectors obtained by the MLP. In short, the channel attention is calculated as:

\[
M(F) = \sigma(MLP(F_{ap}^c + MLP(F_{mp}^c))
\]

where \( MLP() \) represents the MLP operation and \( \sigma() \) denotes the sigmoid function.

![Fig. 2: Diagram of Channel Attention](image)

2.2. Structured Dropout Residual Block (SDRB)

He et al. [11] observed that when deeper networks begin to converge, there will be a degradation problem: as the network deepens, the accuracy quickly degrades after reaching saturation. And, simply deepening the network can...
hinder training. To overcome these problems, the residual network proposed by He et al. shows significantly improved training characteristics, allowing the network depth to be previously unachievable. The residual network consists of some stacked residual blocks, and each residual block can be illustrated as a routine form:

\[ y_i = F(x_i, w_i) + h(x_i) \]
\[ x_{i+1} = \sigma(y_i) \]

where \( x_i \) and \( x_{i+1} \) represent the input and output of the current residual block, \( \sigma(y_i) \) is an activation function, \( F(*) \) is the residual function, and \( h(x_i) \) is an identity mapping function, typically \( h(x_i) = x_i \).

He et al. [13] discussed the effects of diverse combinations in detail and proposed a pre-activation form, as shown in Figure 3 (a). To alleviate the problem of overfitting, we integrate DropBlock [10] into the pre-activated residual block and propose SDRB, as shown in Figure 3 (b). Dropblock is a structured dropout that can effectively alleviate the overfitting problem of fully convolutional neural networks [14]. In this work, we use this proposed SDRB to build SDR-U-Net. If the number of input and output channels is different, we employ \( 1\times1 \) convolution to compress or expand the number of channels.

2.4. Channel Attention Residual Block (CARB)

Channel attention mechanism learns the importance of each feature channel through learning automatically, and uses the obtained importance to enhance features and suppress features that are not important to our retinal vessel segmentation task. In other words, CA can extract channel statistics between channels, thereby further enhancing discriminative ability of the network. Simultaneously, inspired by the success of squeeze and excitation block for classification [15], we integrate CA into SDRB and propose CARB, as shown in Figure 4.

![Diagram of Channel Attention Residual Block](image)

**Fig. 4:** Diagram of Channel Attention Residual Block

### 3. EXPERIMENTS AND RESULTS

#### 3.1. Datasets and Preparation

We used two public retinal fundus image datasets to evaluate our model, they are DRIVE [17] and CHASE DB1 [18]. The DRIVE dataset is collected from a Dutch Diabetic Retinopathy (DR) screening project and contains 40 color fundus images with a resolution of 565×584 pixels. The dataset is partitioned into a training set of 20 images and a testing set of 20 images. CHASE DB1 comes from the British Children's Hearing and Health Research Project, which contains 28 fundus images with a resolution of 999×960 pixels, of which the first 20 images are utilized for training, and the last 8 images are used for testing. The manual annotations of both datasets provided by human experts can be utilized as the ground truth.

To fit our network model, we performed a simple processing on both datasets. We adjusted the size of DRIVE and CHASE DB1 to 592×592 and 1024×1024 by padding it with zero in four margins, respectively. In order to acquire more reasonable results, we crop the segmentation results to the initial size when evaluating.

#### 3.2. Evaluation Metrics

For the purpose that we can estimate the performance of our proposed models, the following metrics are employed: Specificity (Spe), Sensitivity (Sen), F1-score (F1), Accuracy (Acc), and Area Under the ROC Curve (AUC). Among them, Sen, Spe, and Acc can be calculated as follows:

\[ Spe = \frac{TN}{TN + FP} \]
\[ Sen = \frac{TP}{TP + FN} \]
\[ Acc = \frac{TP + TN}{TP + FP + FN + FN} \]

where TP is true positives, which indicates the blood vessel pixels corresponding to the ground truth are accurately classified into vessels in the segmentation results. If they are misclassified as non-vessels, they are represented as true negatives, namely TN. FN stands for false negatives, which indicates that non-vessel pixels corresponding to the ground truth are accurately classified as non-vessels. If they are inferred to be vessels, they are expressed as false positives, namely FP. F1-score considers both Sensitivity and Precision, which is defined as:

\[ F1 = 2 \times \frac{Pre \times Sen}{Pre + Sen} \]

The Area Under the ROC Curve (AUC) can be used to measure the segmentation performance. If the value of AUC is 1, it means flawless segmentation.

#### 3.3. Network Configuration

As mentioned before, we partition the datasets into training and testing sets. In order to further monitor whether our model is overfitting, we randomly select 2 images in the DRIVE and CHASE DB1 training sets respectively as the validation set.

We train this SDR-U-Net and CAR-U-Net from scratch utilizing the training set. For all datasets, we set the number of the feature channel after the first convolutional layer to
16 and utilize the Adam optimizer to optimize our network with binary cross entropy as the loss function. For DRIVE, the training mini-batch is 2, and a total of 200 epochs are trained, of which the first 150 epochs use a learning rate of $1 \times 10^{-3}$ and the latter 50 epochs use $1 \times 10^{-4}$. For CHASE DB1, the training mini-batch is 1, and a total of 150 epochs are trained, of which the first 100 epochs use a learning rate of $1 \times 10^{-3}$ and the next 50 epochs use $1 \times 10^{-4}$.

For the setting of DropBlock, the size of the discard blocks for all datasets is set to 7, and so as to reach the best performance, we set the dropout rates for DRIVE and CHASE DB1 to 0.14 and 0.22, respectively.

| Datasets | Models | Year | Spe | Sen | F1  | Acc | AUC |
|----------|--------|------|-----|-----|-----|-----|-----|
| DRIVE    | U-Net[6]* | 2015 | 0.9820 | 0.7537 | 0.8142 | 0.9531 | 0.9755 |
|          | R2U-Net [19] | 2018 | 0.9813 | 0.7799 | 0.8171 | 0.9556 | 0.9784 |
|          | MS-NFN[7] | 2018 | 0.9819 | 0.7844 | 0.8158 | 0.9567 | 0.9807 |
|          | LadderNet [20] | 2018 | 0.9810 | 0.7856 | 0.8202 | 0.9561 | 0.9793 |
|          | DEU-Net[8] | 2019 | 0.9816 | 0.7940 | 0.8350 | 0.9567 | 0.9772 |
|          | Vessel-Net [21] | 2019 | 0.9802 | 0.8038 | 0.8383 | 0.9578 | 0.9821 |
|          | SDR-U-Net | 2020 | 0.9839 | 0.7953 | 0.8103 | 0.9674 | 0.9828 |
|          | CAR-U-Net | 2020 | 0.9847 | 0.8058 | 0.8202 | 0.9691 | 0.9850 |

| CHASE DB1 | | | | | | |
|-----------|-------------------|-----|-----|-----|-----|-----|
|           | Spe | Sen | F1 | Acc | AUC |
| 0.9701 | 0.8288 | 0.7783 | 0.9578 | 0.9772 |
| 0.9820 | 0.7756 | 0.7928 | 0.9634 | 0.9815 |
| 0.9821 | 0.7978 | 0.8031 | 0.9656 | 0.9839 |
| 0.9821 | 0.8074 | 0.8037 | 0.9661 | 0.9812 |
| 0.9814 | 0.8132 | - | 0.9661 | 0.9860 |
| 0.9828 | 0.8459 | 0.8050 | 0.9742 | 0.9877 |
| 0.9832 | 0.8435 | 0.8063 | 0.9744 | 0.9884 |

### 3.4 Comparison of SDR-U-Net and CAR-U-Net

As mentioned earlier, the only difference between SDR-U-Net and CAR-U-Net is that the latter introduces the channel attention module, so the main content of this section mainly reflects the impact of the channel attention mechanism on the network.

![Fig. 5: Row 1 is for DRIVE dataset. Row 2 is for CHASE DB1 dataset. (a) Color fundus images, (b) segmentation results of SDR-U-Ne, (c) segmentation results of CAR-U-Net, (d) corresponding ground truths.](image)

Examples of the segmentation results of two models are shown in the figures, which are 5 (b) and 5 (c), respectively. For subjective comparison, 5 (d) gives the ground truths for the fundus images. From the segmentation results, CAR-U-Net can get better discrimination ability, and can distinguish targets from small blood vessel structures. We also quantitatively compare the performance of the two models in the last two columns of Table 1. We can get the $F1$, $Acc$ and $AUC$ on DRIVE and CHASE DB1 of CAR-U-Net are 0.99% / 0.13% , 0.17% / 0.02% and 0.22% / 0.07% respectively higher than SDR-U-Net. These results all prove the effectiveness of the attention strategy of channel attention.

### 3.4 Comparisons with the State-of-the-art Models

At last, we compare the proposed CAR-U-Net with several the exiting state-of-the-art models. In Table 1, we sum up the release year of each model and their performance on DRIVE and CHASE DB1 datasets. The results illustrate that, in both datasets, our CAR-U-Net reaches the best performance among all competing models. Specifically, CAR-U-Net has the highest $AUC$ (0.29% / 0.24% higher than the previous best method), the highest accuracy (1.13% / 0.83% higher than the previous best method), the highest sensitivity, and $F1$ and specificity are comparable. The above results clearly demonstrate that CAR-U-Net is a competent method for retinal vessel segmentation.

### 4. CONCLUSION

In this paper, we present a Channel Attention Residual U-Net (CAR-U-Net) for retinal vessel segmentation. First, we use the pre-activated residual block with DropBlock to construct SDR-U-Net. In this process, it can not only reduce the degradation problem, but also effectively alleviate the overfitting problem via DropBlock. More importantly, on the basis of SDR-U-Net, CAR-U-Net considers the relationship between the feature channels, so a channel attention mechanism is introduced to strengthen the network’s discriminative capability. Our experiments show that CAR-U-Net is significantly superior to the state-of-the-art approaches for retinal vessel segmentation on both DRIVE and CHASE DB1 datasets.
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