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Advanced Retinal Blood Vessel Segmentation Technique in Comparison to Other Commonly Used Networks in the U-Net Family

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Abstract
Segmenting retinal vessels is vital for automating the analysis of fundus images to screen and diagnose various retinal vascular diseases, such as diabetic retinopathy, a common complication of diabetes that can lead to sudden vision loss. Automated vessel segmentation offers more efficient and accurate detection of changes compared to manual assessment by an ophthalmologist. The proposed method aims to precisely identify blood vessels in retinal images, simplifying the segmentation process and reducing computational complexity. This approach can improve the accuracy and reliability of retinal image analysis, assisting in diagnosing various eye diseases. The NAU-Net architecture plays a crucial role in segmenting retinal images for conditions like diabetic retinopathy, showing promising results in enhancing segmentation accuracy. Extensive experiments on a retinal segmentation dataset demonstrated that the proposed approach surpassed existing methods in terms of performance and computational efficiency.

Keywords: Artificial Intelligence, Image Segmentation, Retinal Blood Vessel, Colour Fundus Photograph

Introduction

Fundus images serve as a key resource for ophthalmologists in the analysis and diagnosis of various eye diseases [1]. In modern practice, digital color fundus images are utilized, along with digital image processing techniques, to examine different aspects of retinal images, including abnormalities, optic papilla, and retinal vessels [1]. This automated analysis significantly aids ophthalmologists in interpreting images for disease identification, facilitating the diagnosis of conditions like glaucoma, blindness, and macular edema [2-4]. While manual analysis of retinal vessel segmentation from the retinal vessel network is common, it is time-consuming and prone to errors when dealing with large patient databases for eye disease screening [5]. Computerized methods have been developed to enhance the accuracy of retinal vessel segmentation, addressing challenges such as vessels located at image borders, vessels with pathologies, and small vessels [1-6]. These computerized methods aim to effectively address these issues and provide precise images of the retinal vessels [1].

Retinal vessel segmentation involves identifying the blood vessels in the eye's retina from fundus images, playing a critical role in diagnosing and treating various retinal diseases like diabetic retinopathy, age-related macular degeneration, and glaucoma [1]. Previous segmentation methods have been classified into different categories based on their underlying principles. Transform-based methods, also known as frequency-domain methods, analyze images in the frequency domain using Fourier or wavelet transforms, effectively detecting large vessels but facing challenges with tiny vessels [1]. Filtering-based methods utilize image filters like matched filters, Gabor filters, and vesselness filters to enhance vessel visibility, capable of detecting vessels of varying sizes but sensitive to noise and artifacts [1]. Machine learning (ML)-based methods employ classifiers to distinguish vessel pixels from non-vessel pixels, requiring labeled data for training and achieving high segmentation accuracy, yet struggling with small vessel detection due to limited training data [7]. Deep learning (DL), particularly convolutional neural networks (CNNs), has emerged as a prevalent approach for retinal vessel segmentation, showcasing superior performance compared to previous methods. However, these models may encounter difficulties in accurately detecting tiny vessels due to fundus image resolution limitations [1-8]. Ongoing research efforts aim to develop new techniques to address this challenge and enhance the precision of retinal vessel segmentation [1-8].

Current vessel segmentation techniques encounter various obstacles that hinder their effectiveness. One significant challenge is the distinct difference in brightness properties between the optic disc region and the rest of the image [9,10]. The unique brightness of the optic disc margin makes it difficult to identify vessels within the disc, often leading to the misinterpretation of the disc edge as a vascular component in certain retinal images. Additionally, the presence of a combination of high-contrast, wide-width vessels and low-contrast, single-pixel wide vessels in retinal images poses another challenge [11]. These vessels exhibit significant variations in size and shape, making their accurate detection using a single detector a complex task [10-12]. Moreover, existing methods struggle to precisely segment thin or small vessels, impacting their sensitivity in detecting early signs of diseases like diabetic retinopathy and age-related macular degeneration. To overcome these challenges, this study aims to systematically address vessel segmentation issues, particularly those related to tiny vessels. The goal is to develop more efficient methods capable of accurately detecting vessels in the challenging optic disc region and effectively handling the diversity of vessel types and sizes present in retinal images.

In the last twenty years, numerous researchers have developed techniques to address retinal image segmentation challenges, with retinal vessel segmentation methods falling into supervised and unsupervised categories. Supervised retinal vessel segmentation methods involve the classification of pixels as vessels or non-vessels using a trained model. These techniques rely on a database to train the model and obtain segmented vessel images, utilizing ML, DL, and other artificial intelligence approaches [13]. Common classifiers like Random Forest, K Nearest Neighbors, Support Vector Machine, Artificial Neural Networks, and others are employed for vessel image classification [14-18]. While DL models demonstrate superior performance compared to other models, the performance of these image segmentation algorithms is affected by the number of training samples [19]. In addition, datasets of medical images, particularly images of rare cases, are typically insufficient [19]. Therefore, the U-Net was first reported by Ronneberger et al. to improve the performance of small-sample image segmentation [20]. U-Net uses a symmetric architecture to suppress the key image features by down-sampling and to extract low-level features by skip connection and up-sampling [19]. It finally exhibits excellent performance by fusing all the features [19]. Moreover, various variants of U-Net have been developed by modifying or adding modules to improve their accuracy [19]. However, these variants typically achieve excellent performance by fusing multi-scale feature maps with dense links between the encoder and decoder, and as a result, they usually need the expense of computational and time costs [19]. Therefore, to balance the identification performance and computational of the algorithm, a novel U-Net named neighboring attention U-Net (NAU-Net) is designed for fundus image retinal vessel semantic segmentation.

This study aims to integrate the NAU-Net for retinal blood vessel segmentation and evaluate its performance and cost-effectiveness in comparison to established segmentation networks. The goal is to create a precise and economical retinal disease screening tool for future development.

Methods

Experiment and Dataset Preparation

In this research study, we will evaluate the performance of NAU-Net by testing it on the retinal blood vessel segmentation dataset [21]. Additionally, we will compare the segmentation performance of NAU-Net with other models such as SegNet, attention U-Net, and U-Net++, which have network structures similar to our proposed model. The implementation of the proposed model and the comparison models was carried out using the PyTorch framework.

Dataset

The Retinal blood vessel segmentation dataset is a publicly available dataset containing high-resolution retinal fundus images and ground truth labels for retinal blood vessels [21]. These images were captured using advanced imaging technology. Each image is accompanied by detailed pixel-level annotations that precisely identify the locations of blood vessels. The dataset includes pixel-wise annotations in a binary mask format, where blood vessel pixels are marked as 1 and background pixels as 0. To expedite training, the images were resized to 224 x 224 pixels and saved in JPEG format during preprocessing. The dataset of 80 images was divided into training, validation, and test sets, with proportions of 70%, 10%, and 20%, respectively. Data augmentation was omitted to reduce computational expenses and prevent additional noise in the original dataset. Our main goal was to evaluate the performance of the NAU-Net model and compare it with the other prevalent segmentation models. Re-labeling was avoided to mitigate bias, given the absence of external annotators and blinding.

Data Preprocessing

The hue and saturation levels in individual retinal color images display notable variability. Each base image needs to be transformed into an intensity image, which is then standardized to achieve a mean of zero and a variance of one. The standardized intensities are subsequently adjusted to fit within the range of 0 to 255. In human vision, a gamma correction algorithm is employed for image processing. The Contrast Limited Adaptive Histogram Equalization (CLAHE) method is a widely used preprocessing technique for retinal vessel segmentation [22]. It enhances the quality of available data, thereby enhancing the performance of segmentation models. The CLAHE technique is employed to improve the contrast of retinal images by managing noise amplification in neighboring areas and addressing issues related to low-intensity contrast. By enhancing the contrast of retinal images, the CLAHE algorithm maintains overall brightness and color balance, facilitating the differentiation of retinal vessels from the background. This enhancement can improve the accuracy of segmentation models, especially in situations where the contrast between vessels and the background is minimal.

U-Net and its Derivatives

Since its introduction by Ronneberger et al. in 2015, the U-Net has been the basis for various adaptations that have demonstrated broad and robust utility in medical image segmentation, including applications in DR fundus and coronary artery imaging [20]. Figure 1 illustrates the architecture of the U-Net. In addition to the original U-Net, the U-Net family encompasses models such as attention U-Net, residual U-Net, residual-attention U-Net, recurrent residual convolutional neural network based on U-Net, U-Net++, Nested U-Net, among others. These variants incorporate modifications or additions to enhance their capacity for image feature extraction and fusion across different levels.

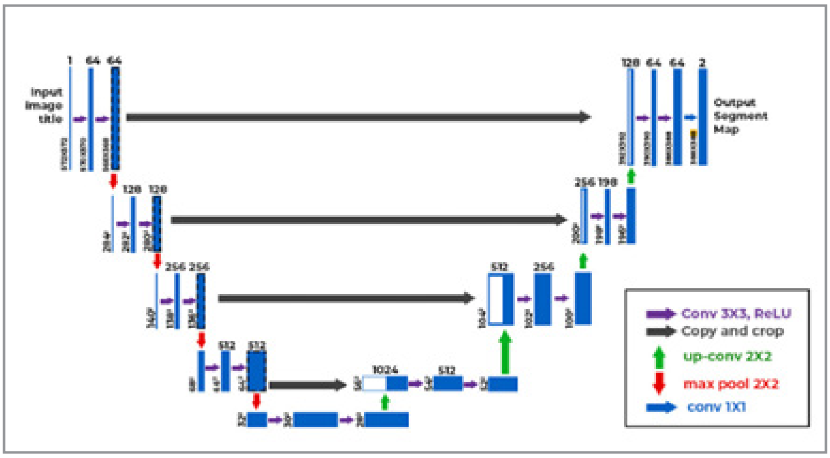

Figure 1: Architecture of U-Net

In 2015, a new network called "U-Net" was developed, featuring an encoder and decoder with a symmetric architecture. The U-Net encoder includes convolution, ReLU activation, and max pooling modules, while the decoder comprises up-convolution, convolution, ReLU activation, and max pooling modules. A cropping operation is used to merge encoder features at corresponding levels during decoding. U-Net's unique approach to image feature extraction and fusion across levels has led to exceptional performance in medical image segmentation, particularly with limited sample sizes.

In comparison to the original U-Net architecture, attention U-Net, U-Net++, and residual-attention U-Net++ exhibit a greater number of connections between low- and high-dimensional feature maps. This integration of features from different levels effectively filters out irrelevant features and enhances the relevant ones. While more intricate nested layers contribute to improved performance, they also result in a higher parameter count and increased computational complexity. To strike a balance between computational efficiency and cost, we introduce the NAU-Net for tasks such as diabetic retinopathy and other medical image segmentation. In this novel network, neighboring high- and low-dimensional feature maps are merged using an attention gate to enhance target features at a reduced computational expense.

NAU-Net

Figure 2 illustrates the structure of the NAU-Net. This network incorporates four attention gates to align the feature maps of the encoder with those of the decoder at various levels. The attention gates receive inputs from the adjacent feature maps of the encoder and decoder at corresponding levels. By leveraging these attention gates, comparable feature maps are merged, enhancing the desired features. Unlike U-Net++ and residual attention U-Net++, this network solely utilizes neighboring layers and excludes inner layers, resulting in reduced computational expenses.

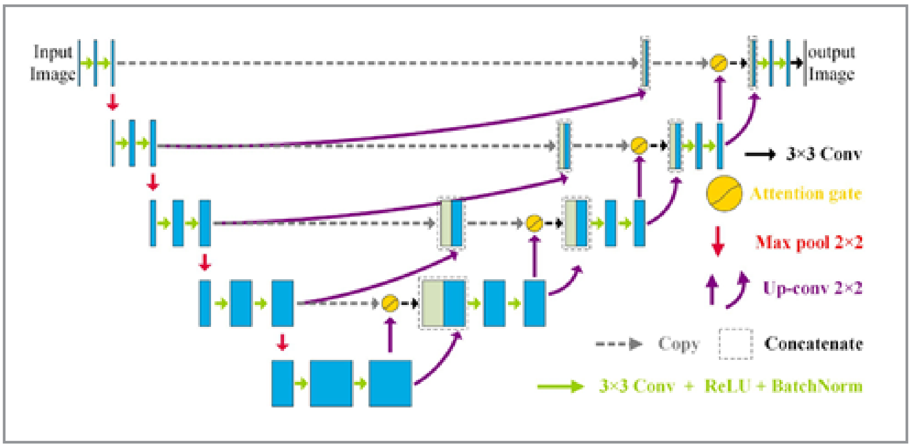

Figure 2: Architecture of NAU-Net

In order to seamlessly merge the feature maps and maintain a consistent output size with the input image, the traditional approach involves using a 3×3 kernel size with a stride and padding of one. Following the convolution process, additional operations such as ReLU activation, batch normalization, and max pooling are carried out. The max pooling is typically set at 2×2 with a stride of two. The up-convolution step comprises up-sampling, a 2×2 convolution with a stride and padding of one, batch normalization, and ReLU activation. Lastly, a 3×3 convolution operation is employed to convert the filtered image into a single channel.

As the number of convolutional layers in the encoder increases, more detailed features of the target are gradually lost. While there is some similarity between adjacent high-dimensional feature maps in the encoder, the connection between distant maps weakens. To enhance shared features in the maps efficiently, the NAU-Net utilizes attention to fuse only the two neighboring feature maps of the encoder. Prior to combining the feature maps of the encoder and decoder, the two adjacent feature maps of the encoder are fused. Given the differing dimensions of these neighboring feature maps, the lower-dimensional map undergoes an up-convolution operation before being concatenated. Following the processing of the $L+1$ level feature map with dimensions $W \times B \times 2 \times ch$ through up-sampling, convolution, batch normalization, and ReLU, a new feature map matching the dimensions of the Lth map is generated. This new feature map is then concatenated with the Lth feature map.

The encoder typically holds detailed features of the target in high-dimensional feature maps, while the decoder contains broader texture information in low-dimensional feature maps. To enhance identification accuracy, NAU-Net utilizes an attention mechanism to extract and combine multi-scale features from both low- and high-dimensional feature maps of the target. These feature maps are fed into a shared attention gate. In this research, binary cross-entropy and Dice loss have been chosen as loss functions to assess segmentation performance.

Training of the Segmentation Networks

The Adam optimizer was utilized, with its learning rate adjusted through the CosineAnnealinLR scheduler. The maximum number of iterations was set at 10, with a minimum learning rate of 0.0001 specified for the scheduler. The total number of epochs conducted was 140, with a batch size of four chosen for the process.

Evaluation Metrics

This study introduced commonly used evaluation metrics, such as the Dice score, IoU, accuracy (AC), and precision (PC), to display and compare segmentation performance. These metrics are calculated as follows: Dice score (DC) = 2TP / (FP + FN + 2TP); IoU = TP / (FP + FN + TP); AC = (TP + TN) / (TP + TN + FP + FN); PC = TP / (TP + FP), where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively. Additionally, the computational cost was assessed by comparing the total number of parameters and GPU memory requirements of the models.

Results

Computational Cost Comparison

To evaluate the computational efficiency of NAU-Net, a comparison was conducted among various models including SegNet, attention U-Net, U-Net++, and NAU-Net based on parameters and memory requirements. It was observed that the computational complexity and cost of the U-Net models are higher in comparison to SegNet in terms of the number of parameters required (32.31-35.11 VS 25.78 in SegNet) and the memory requirement. However, it is noteworthy that SegNet typically necessitates a larger number of training samples to achieve satisfactory accuracy, resulting in much increased training expenses eventually. Our experiment discovered that the parameter count in NAU-Net is slightly greater than that of attention U-Net and U-Net++ (35.11 in NAU-Net VS 32.31-34.89). The total memory usage of NAU-Net is slightly higher than attention U-Net and lower than U-Net++. The computational complexity of NAU-Net is likely to fall between that of attention U-Net and U-Net++.

Retinal Blood Vessel Segmentation

The NAU-Net exhibited an accuracy of 0.9523, precision of 0.8452, dice score of 0.7987, and Jaccard score of 0.6447. In comparison, the SegNet model achieved an accuracy of 0.8659, precision of 0.7021, dice score of 0.5046, and Jaccard score of 0.3979. Furthermore, the Attention U-Net achieved an accuracy of 0.9488, precision of 0.8186, dice score of 0.7765, and Jaccard score of 0.6356. Lastly, U-Net++ demonstrated an accuracy of 0.8865, precision of 0.7245, dice score of 0.5738, and Jaccard score of 0.4189. The performance metrics of the NAU-Net and other baseline segmentation models for retinal blood vessel segmentation are presented in Table 1.

Table 1: Performance of different segmentation networks

	Accuracy	Precision	Dice score	Jaccard score (IoU)
SegNet	0.8659	0.7021	0.5046	0.3979
Attention U-Net	0.9488	0.8186	0.7765	0.6356
U-Net++	0.8865	0.7245	0.5738	0.4189
NAU-Net	0.9523	0.8452	0.7987	0.6447

Moreover, the suggested NAU-Net demonstrated superior ability in detecting minute and small retinal blood vessels in the fundus compared to the attention U-Net and U-Net++. This suggests that the fusion process of neighboring feature maps effectively captures intricate features from the encoder, leading to the NAU-Net exhibiting enhanced performance in segmenting tiny and small retinal blood vessels when compared to the attention U-Net and U-Net++.

Discussion

In this research, a modified U-Net named NAU-Net was discovered to be highly effective and accurate for segmenting retinal blood vessels in images, striking a balance between identification performance and computational cost. The NAU-Net integrates neighboring high- and low-dimensional feature maps from both the encoder and decoder using four attention gates in the new network. This enhancement boosts common target features in the encoder's high-dimensional feature maps and merges them with the decoder's low-dimensional feature map through the attention gates. Unlike U-Net++, the NAU-Net excludes inner layers and solely utilizes neighboring layers, resulting in improved identification performance at a reduced computational cost.

Experimental results on an open dataset for retinal blood vessel segmentation demonstrate that NAU-Net outperforms SegNet, attention U-Net, and U-Net++ in terms of Dice score, IoU, accuracy, and precision, while maintaining a computational cost between attention U-Net and U-Net++. Therefore, NAU-Net offers superior performance with a cost-effective approach, presenting a novel and efficient method for segmenting retinal blood vessels in fundus images and serving as an automated tool for diagnosing retinal eye diseases such as diabetic retinopathy and hypertensive retinopathy.

The segmentation of retinal vessels has garnered significant attention, yet numerous challenges persist. Firstly, blood vessels exhibit diverse forms, diameters, and shades of grey [23]. Secondly, the contrast between certain vessels and their surroundings is relatively minimal [24]. Lastly, there are anomalies that present as bright patches amidst dark and narrow spaces, resembling blood vessels [23]. The NAU-Net offers a potential alternative solution to address these issues faced by current segmentation networks.

The sophisticated vessel segmentation technique holds various applications in patients with eye conditions. Initially, it supports the monitoring of disease progression through the periodic capture of fundus images and analysis of vascular alterations, assisting in identifying disease advancement and the necessity for treatment modifications [25]. Additionally, the technique contributes to the customization of treatment strategies by enhancing physicians' comprehension of lesion location and severity, enabling informed decisions on the optimal treatment approach, including laser treatment, drug therapy, or surgical intervention [25].

Future endeavors will focus on developing an end-to-end automatic diagnosis model by integrating the proposed architecture with other classification models, as well as enhancing the architecture for multitask image segmentation of fundus images containing various types of lesions.

Conclusion

In summary, our research introduces a promising method, the NAU-Net, to enhance retinal vessel segmentation, providing the opportunity for increased accuracy and reliability in medical image analysis.

Conflict of interest

All authors have disclosed no conflict of interests

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This study received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Data Availability Statement

All data is publicly available and can be retrieved from open-source platforms like Google Dataset Search and Kaggle. The link to the dataset used was also cited in the reference.

Ethics Statements and Patient Consent for Publication

Not required

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