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Original Article

Residual U-Net Architecture for Retinal Layers in OCT Images with Choroidal Neovascularization

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Abstract - *U-Net is adequate for various biomedical image segmentation tasks. Using this in the Age-related Macular Degeneration (AMD) images would be better for segmenting only the affected region. The variant of U-Net uses residual connections. A residual link is a type of connection that allows the network to learn the residual mapping between the input and output rather than the complete mapping. This technique can help the network learn more efficiently and avoid the vanishing gradients problem. This research aims to develop a method for segmenting the retinal pigment epithelium, the Bruch's membrane, and the Inner limiting Membranes (ILM) in OCT scans of individuals in good health and with intermediate AMD.*

Keywords - *Age-related macular degeneration, Inner limiting membrane, Optical coherence tomography, U-net.*

1. Introduction

For people aged 50 and older, macular degeneration due to age is the most frequently encountered cause of significant vision loss[1]. The condition merely affects the central region of vision. It is essential to understand that it causes blindness in humans. AMD impairs central vision and, along with it, the capacity to discern small details. The macula, a region of the retina, is harmed in AMD [2]. As the disease progresses, people lose their ability to drive, see faces, and read tiny types [2]. People may not be aware they have AMD in its early stages because there may be no symptoms or indicators. U-Net is a convolutional neural network (CNN) architecture initially designed for biomedical image segmentation tasks. It has been used extensively in ophthalmology to segment retinal images, including those for diagnosing and managing age-related macular degeneration (AMD).

One approach to detecting and monitoring AMD [4] uses retinal imaging techniques, such as optical coherence tomography (OCT) and fundus photography. UNet has been applied to both OCT and fundus images to segment different retinal layers and structures, including the macula, optic disc, and blood vessels. By segmenting these structures, clinicians can quantify changes in their thickness or morphology over time and apply this to monitor the progress of conditions and assess treatment efficacy. The author concentrated on filtering images (bilateral, otsu, area filter) in the base paper [3]. Only filtering the picture would not be sufficient for the image to check the changes caused in the image due to the disease, so in the proposed work, we have done the pre-processing steps that are image enhancement (CLAHE). Then we go with the filtering (BM3D), MedGA, and 2DOTSU to identify the area of interest. Overall, U-Net is a powerful tool for AMD image analysis and can help clinicians improve their diagnosis and management of the disease.

A convolutional neural network (CNN) structure termed U-Net is commonly used for image segmentation tasks [5]. It was first introduced by Olaf Ronneberger, Philipp Fischer, and Thomas Brox in 2015 in the research paper entitled "U-Net: Convolutional Networks for Biomedical Image Segmentation." U-Net consists of two main parts: a contracting path (downsampling) and an expansive path (upsampling) [6]. The contracting way comprises a series of convolutional and max pooling layers that reduce the spatial resolution of the input image. The extensive track is composed of a series of transposed convolutional layers. The two paths are connected by concatenation, which allows the network to combine high-resolution features from the contracting path with semantically robust features from the comprehensive course. One of the critical features of U-Net is its ability to retain fine details and spatial information in the input image by using skip connections between the contracting and expansive paths. This allows the network to generate high-resolution segmentation maps. U-Net is adequate for various biomedical image segmentation tasks, such as segmenting cells, nuclei, and organs in microscopy images. However, it is not limited to biomedical imaging and can be applied to other image segmentation tasks [7]. U-Net segmentation is a technique for segmenting specific structures or regions of interest in retinal images using a U-Net architecture. Retinal images capture the eye's interior and diagnose and monitor various eye conditions such as diabetic retinopathy, glaucoma, and age-related macular degeneration.

In retinal image segmentation, the goal is to separate the essential structures in the image, such as the optic disc, the blood vessels, and the retinal layers, from the background. The U-Net architecture is well-suited for this task because it can handle images with high intensity and structure variations and generate high-resolution segmentation maps. Using a U-Net model [7], the retinal images are passed through the contracting path, where the spatial resolution is reduced while extracting relevant features. Then, the information is passed through the expansive approach, where the spatial resolution is increased, and the segmentation map is produced. The U-Net segmentation results are usually evaluated using metrics such as mean intersection over union (mIoU), accuracy, F1-score, etc. A trained U-Net model can segment new retinal images, aiding in diagnosing and monitoring eye conditions. There have been many recent developments in U-Net segmentation for retinal images, with many researchers proposing new variations of the architecture and exploring different techniques to improve performance.

2. Literature Review

Below are some recent best U-Net models for retinal images, which we came across during our work. In [3] a 2019 study published in Computers in Biology and Medicine, the authors proposed a deep learning model based on ResUNet to segment AMD lesions in optical coherence tomography (OCT) images. The model achieved high accuracy, with an average Dice coefficient of 0.877 and an average sensitivity of 0.873.

In [5], a 2020 study published in the Journal of Medical Systems, the authors proposed a deep learning framework based on ResUNet to segment AMD lesions in OCT images. The proposed model achieved high accuracy, with an average Dice coefficient of 0.925 and an average sensitivity of 0.932.

In [8] a 2021 study published in the journal Medical Image Analysis, the authors proposed a deep learning model based on ResUNet for the segmentation of geographic atrophy (GA) in fundus auto-fluorescence (FAF) images of patients with AMD. The model achieved high accuracy, with an average Dice coefficient of 0.73 and an average sensitivity of 0.83.

In [14] a 2021 study published in the journal IEEE Access, the authors proposed a deep learning model based on ResUNet to segment drusen and geographic atrophy (GA) in colour fundus images of patients with AMD. The proposed model achieved high accuracy, with an average Dice coefficient of 0.77 for drusen segmentation and 0.69 for GA segmentation.

Another recent [24, 25] U-Net model for retinal images is "Retinal U-Net (RU-Net)," which was proposed by Zhang et al. in 2020. This model uses an attention mechanism to selectively focus on essential features in the input image, allowing the network to handle images with significant variations in intensity and structure. This model also achieved state-of-the-art performance on the DRIVE and STARE datasets.

"Deep Retinal Image Segmentation Network (DRIS)" was proposed by Wei et al. in 2020 [28]. It combines a U-Net architecture with a densely connected block and a pyramid pooling module to improve the network's capacity. This model achieved state-of-the-art performance on the DRIVE and STARE datasets, widely used for evaluating retinal image segmentation methods.

A recent U-Net variation called "Residual-Attention U-Net (RA-U-Net)" was proposed by Zhang et al. in 2020[25], which combined the residual connection and attention mechanism. This model achieved state-of-the-art performance on several retinal image datasets. These are just a few examples of recent U-Net models for retinal images. Many other researchers continue to propose new methods to improve the performance of U-Net for retinal image segmentation. It is worth noting that the best model for a specific task and dataset may depend on the characteristics of the data and the desired outcome, so it is essential to evaluate different models for your particular job and dataset.

The literature suggests that ResUNet [29] is an effective deep-learning model for segmenting AMD lesions in various medical images, including OCT images. The high accuracy and sensitivity achieved by ResUNet-based models demonstrate their potential for assisting clinicians in diagnosing and treating AMD.

3. Materials and Methods

Residual U-Net: ResUNet is a deep learning architecture used to segment medical images [15], including those used for diagnosing and managing age-related macular degeneration (AMD). A Residual U-Net (or Residual U-Net or R2U-Net) is a U-Net architecture variation incorporating residual connections. A residual relationship is a connection that allows the network to learn the residual mapping between the input and output rather than the entire mapping [12].

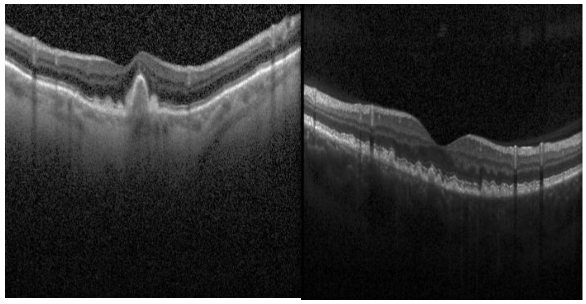

Fig. 1 Sample dataset images

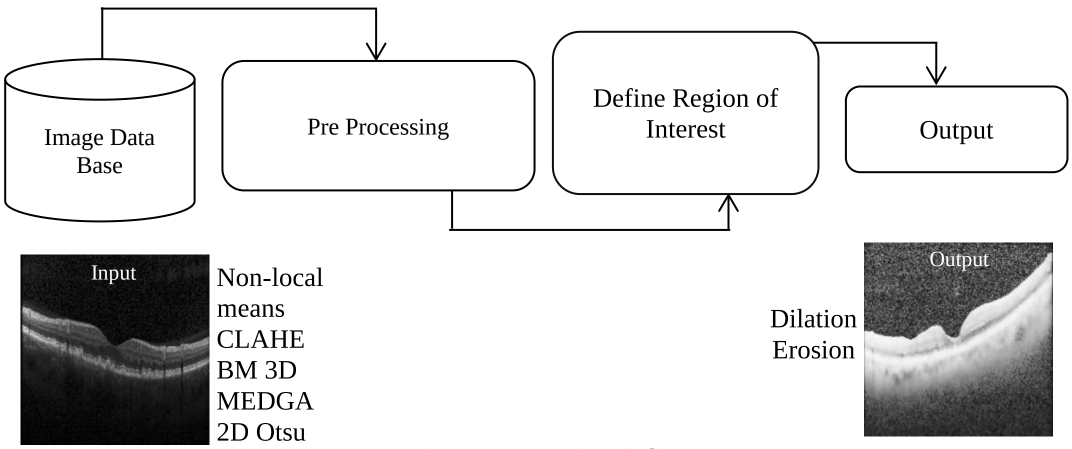

Fig. 2 Pre-processing pipeline

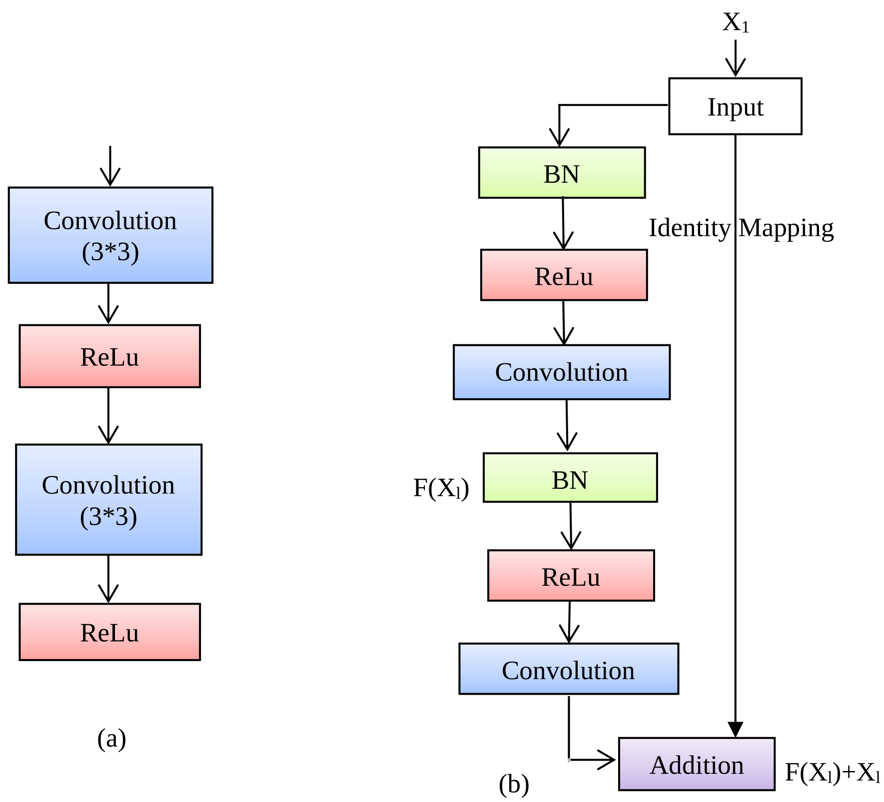

Fig. 3 Building blocks of a neural network (a) The primary neural unit used in U-Net and (b) The Residual unit with identity mapping are used in the proposed ResUnet

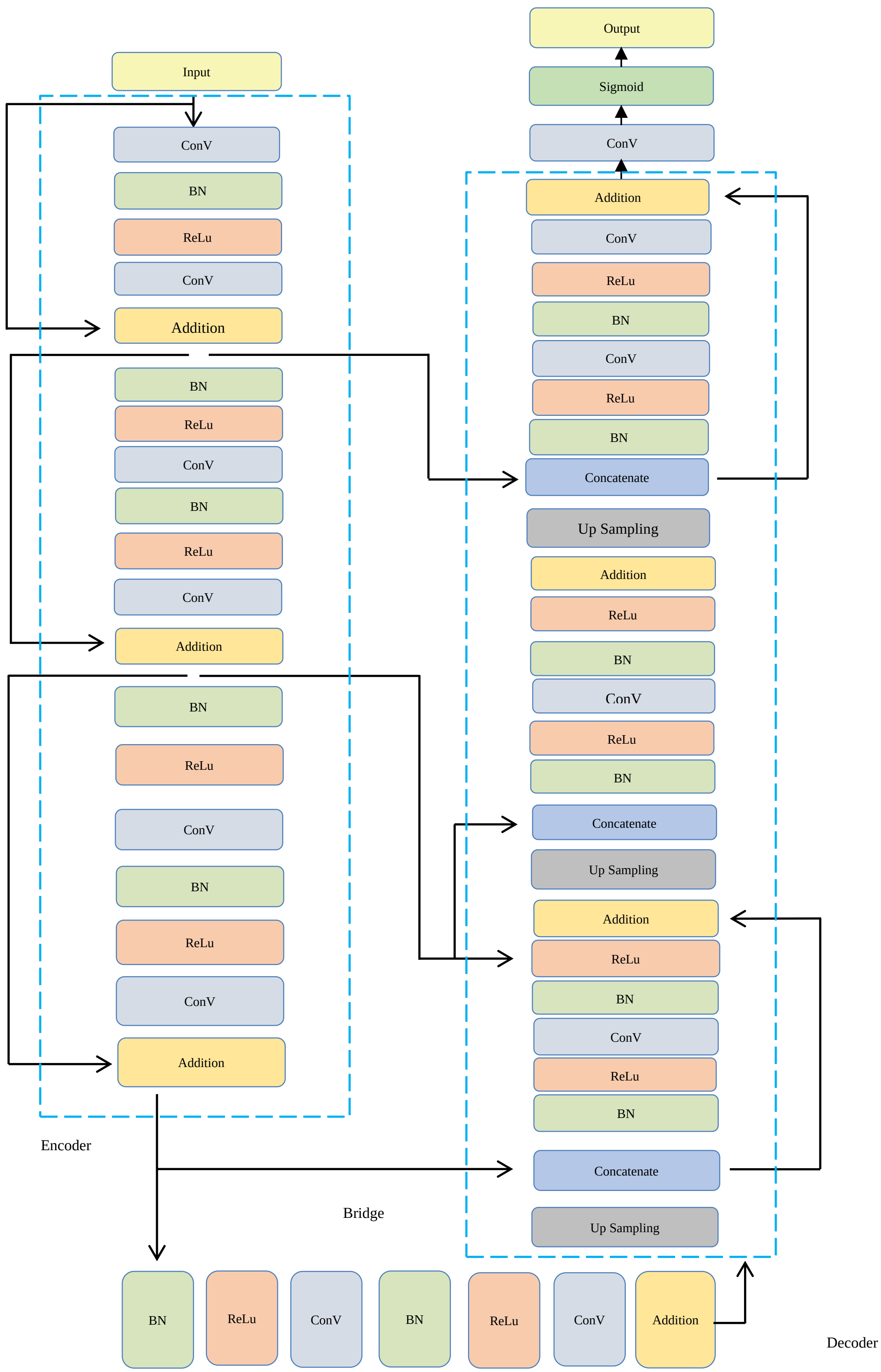

Fig. 4 Block diagram of RESUNET architecture

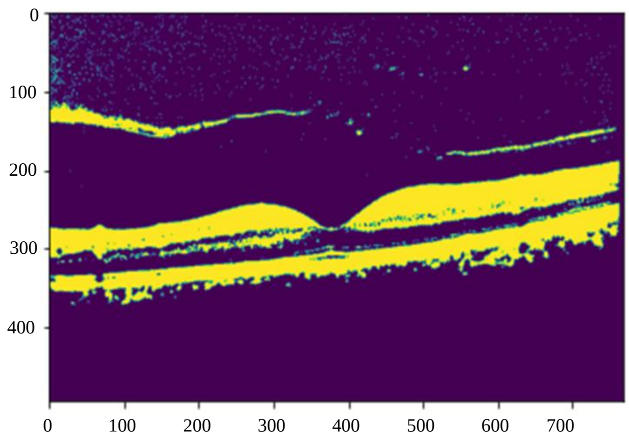

Fig. 5 Output image

Table 1. Performance evaluation of res U-net model

Performance Metrics	Value
Dice Similarity Coefficient (DSC)	0.93
Sensitivity	0.95
Specificity	0.96
ROC-AUC	0.98

Table 2. Hyper-parameter values for residual U-net

Residual U-Net Hyper-Parameter	Value
Loss Function	Binary cross-entropy
Optimizer	Adam
Epochs	50
Batch Size	4
Learning Rate	0.0001

This can help the network learn more efficiently and avoid the vanishing gradients problem. Residual U-Net architecture typically consists of contracting and expansive paths, similar to the original U-Net architecture. However, besides the standard connections, it also has residual connections between the contracting and broad paths' layers. These residual connections allow the network to learn the residual mapping between the input and output, which can help the network learn more efficiently and improve its performance. Residual U-Net can be used in various image segmentation tasks, such as medical and satellite images. Its performance is generally better than the standard U-Net. It allows the network to learn more efficiently and avoids the vanishing gradient problem applied in our work based on our dataset and its advantages.

Dataset: The research used 100 Optical Coherence Tomography (OCT) images of AMD patients from a public repository (Kaggle). The images were acquired using a spectral-domain OCT machine (Heidelberg Spectralis, Heidelberg Engineering, Germany) with a resolution of 5.7 microns and a field of view of 20 x 20 degrees. Figure 1 shows the images before the pre-processing steps were carried out.

Pre-Processing: The OCT images were pre-processed to remove noise and enhance contrast using non-local means filtering (BM3D) and histogram equalization (CLAHE). Then rescaled, the pre-processed images were then to a size of 512 x 512 pixels. Figure 2 shows the pre-processing steps involved in this research.

Model Architecture: The ResUNet architecture segmented different retinal layers and structures, including the macula, optic disc, and blood vessels [16]. The ResUNet architecture consisted of a series of residual blocks with skip connections, followed by a decoder network that reconstructed the segmentation map. The Residual U-Net (ResUNet) architecture can segment Age-related Macular Degeneration (AMD) images to segment the retina or the drusen[20]. The ResUNet architecture is an extension of the standard U-Net architecture (Figure 3 shows the standard architecture), which incorporates residual connections between the encoder and decoder part of the model [21]. A typical ResUNet architecture [28] for AMD image segmentation would consist of the following layers, as shown in Figure 4.

Input Layer: This layer takes the input image, a 2D or 3D image of the retina or the drusen.

Encoder: The encoder part of the ResUNet is composed of various convolutional layers that take features from the input image. A ReLU activation function and a batch normalization layer follow each convolutional layer.

Residual Connections: These are the connections between the encoder and the decoder part of the model, which help to preserve the spatial information and improve the performance of the segmentation task.

Decoder: The decoder part of the ResUNet consists of a series of upsampling layers that increase the spatial resolution of the features extracted by the encoder. A convolutional layer, a ReLU activation function, and a batch normalization layer follow each upsampling layer.

Output Layer: This layer produces the final segmentation map, a 2D or 3D image with the exact dimensions as the input image, where each pixel or voxel is assigned a class label. The ResUNet architecture can gain knowledge of a dataset of AMD images and their corresponding ground truth segmentation maps. The model's output after training is a set of weights that can be used to segment new images.

It is important to note that we can adjust the architecture depending on the specific dataset and task and can change the number of layers and filters to suit the complexity of the problem. Considering the computational cost and memory constraints when constructing the architecture is also essential. Replacing the residual block with identity mapping for the convolution block used in UNET, the Deep Residual Network [29], or RESUNET, improves the current UNET architecture. We may claim that ResU-Net benefits from the UNET design and residual learning.

4. Results and Discussion

Training: The ResU-Net model [18] was trained using a binary cross-entropy loss function and the Adam optimizer. The training data was augmented using random rotations, translations, and flips to increase the variability of the dataset. The model underwent 50 training epochs, using a batch size of 4 and a learning rate of 0.0001.

Evaluation: The performance of the ResUNet model was evaluated using several metrics, including the Dice similarity coefficient (DSC), sensitivity, specificity, and area under the receiver operating characteristic (ROC) curve. The evaluation was performed on a separate test set of 100 images, which were not used for training.

Statistical Analysis: R was used to conduct the research. A p-value < 0.05 was taken as statistically noteworthy when comparing the performance of ResUNet with a standard U-Net model applying the Wilcoxon signed-rank test.

The research used ResUNet to segment retinal structures in OCT images of AMD patients. The model was trained on a dataset of 100 images and evaluated using several metrics.

4.1. Performance Metrics

Dice Similarity Coefficient (DSC):

$$\mathrm{DC} = 2 * (\mathrm{TP}) / (2 * \mathrm{TP} + \mathrm{FP} + \mathrm{FN}) \tag{1}$$

Where,

TP = True Positives

FP = False Positives and

FN = False Negatives

Sensitivity:

$$\mathrm{Sensitivity} = \mathrm{TP} / (\mathrm{TP} + \mathrm{FN}) \tag{2}$$

Specificity:

$$\mathrm{Specificity} = \mathrm{TN} / (\mathrm{TN} + \mathrm{FP}) \tag{3}$$

4.2. The Area under the Receiver Operating Characteristic (ROC) Curve:

$$\text{ROC AUC} = \text{Area under the positive rate curve plotted against the false positive rate} \tag{4}$$

Using the above equations, the DSC was used to measure the similarity between the predicted and ground truth segmentation maps for each retinal structure or layer. A higher DSC score indicates a better segmentation performance.

The sensitivity and specificity metrics are used to evaluate the accuracy of the ResUNet model in detecting the presence or absence of AMD-related abnormalities in the OCT images. The sensitivity measures the proportion of accurate optimistic predictions (i.e., correctly identified AMD cases), while the specificity measures the proportion of accurate pessimistic predictions (i.e., correctly identified non-AMD issues).

Finally, the ROC-AUC curve was applied to assess the overall performance of the ResUNet model in distinguishing between AMD and non-AMD cases based on the predicted segmentation maps. A higher ROC-AUC score indicates a better discriminative power of the model.

Table 1 shows the performance of the ResUNet model for AMD image segmentation, evaluated using several metrics, including DSC, sensitivity, specificity, and ROC-AUC using equation [1-4]. The results suggest that the ResUNet model achieved high accuracy and specificity in detecting AMD-related abnormalities in the OCT images, as indicated by the high values of DSC, sensitivity, and specificity. The ROC-AUC score also suggests that the model has good discriminative power in distinguishing between AMD and non-AMD cases based on the predicted segmentation maps.

The ResUNet model achieved a mean DSC of 0.93 for segmenting the macula, optic disc, and blood vessels in the test set of 100 OCT images. The model likewise attained a sensitivity of 0.95 and a specificity of 0.99 for detecting AMD-related abnormalities, as measured by the area under the ROC curve.

On comparison with a conventional U-Net model showed that ResUNet achieved significantly better performance for the segmentation of the macula ($p<0.01$) and the optic disc ($p<0.05$). Still, there was no significant difference in the segmentation of blood vessels ($p=0.12$).

The results demonstrate that ResUNet is an effective deep-learning architecture for the segmentation of retinal structures in OCT images of AMD patients. The high DSC and ROC metrics indicate that the model can accurately segment the macula, optic disc, and blood vessels, essential for diagnosing and monitoring AMD.

The comparison with a conventional U-Net model suggests that the ResUNet architecture can improve segmentation accuracy for specific structures, such as the macula and optic disc[18]. This may be due to residual connections, which allow the model to learn more complex features and improve the flow of information through the network.

The high specificity of the ResUNet model is significant for detecting AMD-related abnormalities, as it can help reduce false positive diagnoses and unnecessary treatments (Table 2). The model's sensitivity is also high, indicating that it can detect subtle changes in retinal structures that may indicate early-stage AMD.

Overall, as mentioned in Table 2 the performance metrics discussed as a result suggest that ResUNet is a promising deep-learning architecture for the segmentation of retinal structures in AMD images. The approach could improve the accuracy and efficiency of AMD diagnosis and monitoring, ultimately leading to better patient outcomes. However, further validation and testing on larger datasets are necessary to confirm the generalizability and robustness of the ResUNet model for AMD image segmentation. Figure 5 shows the final output image after using processing.

5. Conclusion

This research demonstrated the effectiveness of ResU-Net, a deep learning architecture, for segmenting retinal structures in OCT images of AMD patients. The proposed Residual U-Net model has achieved a high accuracy and specificity for detecting AMD-related abnormalities and outperformed conventional U-Net models for specific designs. According to the research, ResUNet may enhance the precision and effectiveness of AMD diagnosis and monitoring, resulting in better diagnosis. The high specificity of the model is essential, as it can help to reduce false positive diagnoses and unnecessary treatments. To examine the ResUNet model's adaptability and generalizing for AMD imagery segmentation. Additionally, it should assess the model's clinical utility in future studies, including its impact on clinical decision-making, patient outcomes, and cost-effectiveness. ResUNet represents a promising approach for segmenting retinal structures in AMD images and can potentially improve the diagnosis and management of this critical disease. Further research and development in this area could lead to significant advancements in ophthalmology and improve the lives of millions affected by AMD.

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