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PAPER

Segmentation of Retinal Images Using Improved Segmentation Network, MesU-Net

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ABSTRACT

Given the immense importance of medical image segmentation and the challenges associated with manual execution, a diverse range of automated medical image segmentation methods have been developed, primarily focusing on specific modalities of images. This paper introduces an innovative segmentation algorithm that effectively segments exudates, hemorrhages, microaneurysms, and blood vessels within retinal images using an enhanced MesNet (MesU-Net) model. By combining the MES-Net model with the U-Net model, this approach achieves accurate results in a shorter period. Consequently, it holds significant potential for clinical application in computer-aided diagnosis. The IDRID and DRIVE datasets are utilized to assess the efficacy of the proposed model for retinal segmentation. The presented method attains segmentation accuracy rates of 97.6%, 98.1%, 99.2%, and 83.7% for exudates, hemorrhages, microaneurysms, and blood vessels, respectively. This proposed model also holds promise for extension to address other medical image segmentation challenges in the future.

KEYWORDS

Computer Aided Detection, classification, optical coherence tomography, diabetic retinopathy, exudates

1 INTRODUCTION

Diabetic Retinopathy [1] is a disorder in which diabetes affects the retina. It impacts approximately 80 percent of individuals with diabetes who have had the condition for over 20 years. Anomalies in the inner and outer retinal components due to Macular Telangiectasia [2] eventually lead to vision loss. With proper eye care and monitoring, it is possible to prevent at least 90 percent of new cases. Retinal disease stands as a significant global cause of severe vision loss and blindness, prompting widespread attention. The retina, a membrane layer at the back of the eye, can

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be visualized as a retinal image through a fundus camera. Figure 1 displays images of both healthy and unhealthy retinas.

Non-Proliferative Diabetic Retinopathy (NPDR) is an early-stage condition often devoid of symptoms. In Proliferative DR, damaged blood vessels close off, leading to the formation of new, abnormal blood vessels in the retina. These blood vessels can also leak into the vitreous, the transparent jelly-like fluid filling the center of the eye. Fundus imaging offers an objective means to document observations, including the identification of microaneurysms. An automated method for analyzing retinal images is crucial, particularly for efficiently managing the large-scale screening of images. Certain areas in CAD for diabetic retinopathy require improvements [3], such as refining the determination of the Optic Disc boundary from blurred edges and accurately extracting blood vessels and exudates from retinal images. Figures 2–5 respectively illustrate annotated blood vessels, hemorrhages, exudates, and microaneurysms in sample retinal images. The identification of these features in retinal images aids ophthalmologists in evaluating the extent and severity of diabetic retinopathy.

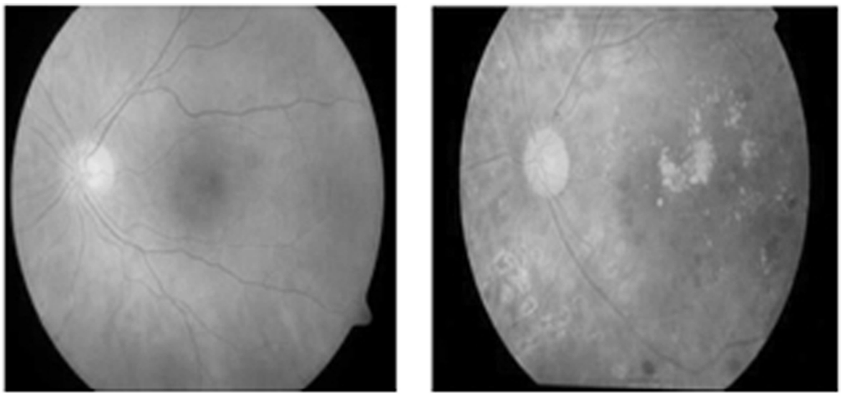


Fig. 1. Retinal images of (a) Healthy retina (b) Unhealthy retina

Numerous eye disorders, along with systemic conditions like diabetes and hypertension, are diagnosed and managed using retinal imaging. Timely identification of eye diseases can prevent vision loss. However, the growing number of patients is placing an increasing burden on ophthalmologists. Therefore, the development of a segmentation model capable of automatically and accurately segmenting retinal images for diagnosing eye diseases holds great promise for medical science. Exudates, which result from the accumulation of lipoproteins exiting the circulatory vasculature in patients with diabetes, serve as early signs of diabetic retinopathy, making their prompt detection crucial. The segmentation of fundus images has become indispensable in ophthalmology's diagnostic path. This assists human experts in determining the presence of abnormalities within the images, and such systems can provide experts with a second opinion. While there are numerous models [4] available for retinal image segmentation, models that reliably produce accurate results are fewer in number. An efficient model capable of accurately segmenting retinal images would be immensely beneficial to society. In this paper, we propose a research-based solution designed to yield faster results, potentially alleviating the workload on ophthalmologists in disease prediction and offering a valuable contribution to humanity.

Fig. 2. Retinal image and its annotated blood vessels

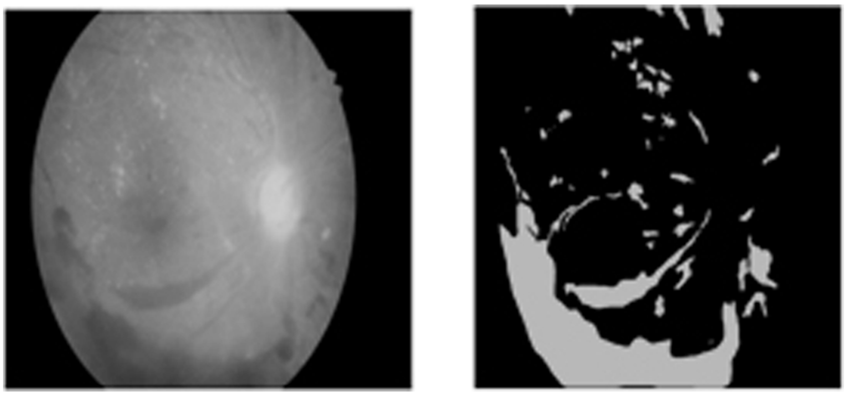


Fig. 3. Hemorrhages in retinal image and its ground truth

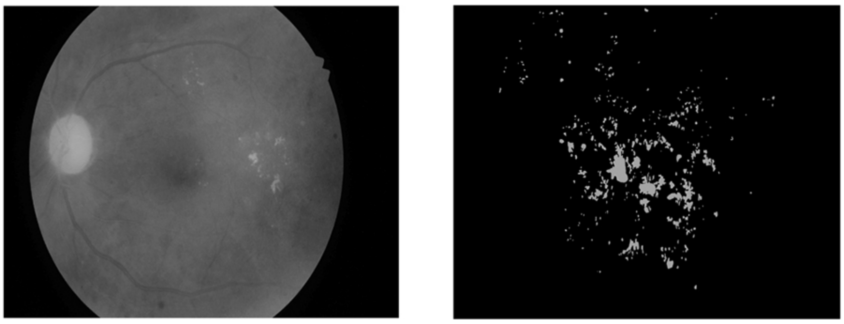


Fig. 4. Exudates in retinal image and its ground truth

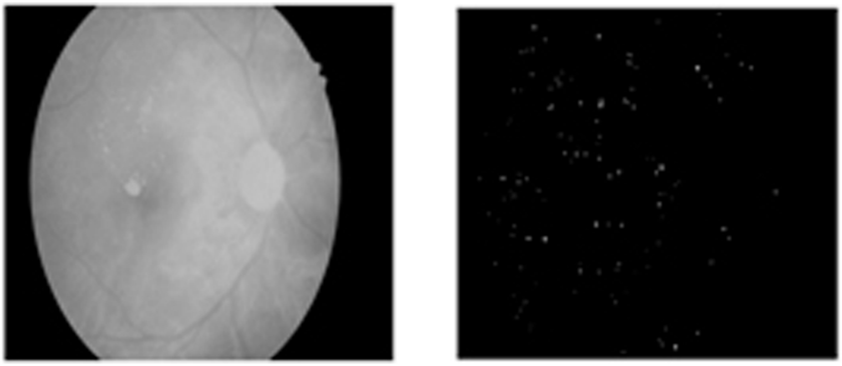


Fig. 5. Micro aneurysm in retinal image and its ground truth

We strive to address the following questions in this research, including a) What are the most recent state-of-the-art techniques for automatically segmenting retinal images using sophisticated deep learning architectures U-Net and MesNet? b) How effective is the ensemble of two segmentation networks in improving the accuracy of segmentation in comparison to individual networks, considering the complementary strengths and potential synergies between the two models? c) How does the performance of the MesU-Net model, a newly proposed deep neural architecture, surpass identical models with an equivalent number of network parameters in terms of segmentation accuracy and other performance metrics?

2 RELATED WORKS

There are numerous existing algorithms for effectively segmenting retinal images. The algorithms for segmentation fall into two categories: supervised and unsupervised. The unsupervised algorithms reveal correlations, patterns, and categories among the data samples to create segmentation results. The model is trained using labeled samples in supervised methods, which then produces the output. The traditional machine learning strategy and the deep learning approach are parts of the supervised learning process. For the machine learning models, it requires a manual design of the pixel features. Algorithms such as SVM, Ada Boost, Random Forest, etc. work on the basis of these extracted feature vectors.

Much work has gone into using segmentation networks to find anomalies in retinal fundus images. Different techniques have recently been developed in order to categorize and identify exudates in retinal images. For the classification and detection of exudates, three separate pretrained convolution networks, namely, Inception-v3, VGG-19, and ResNet-50, were combined in [5]. DIARETDB1 and e-Ophtha both had an accuracy of 98.43% and 98.91% respectively in this investigation. For the purpose of conducting exudate segmentation of retinal images, a U-Net based network architecture is presented in [6]. It employs Simple Linear Iterative Clustering algorithm to generate patches of exudates. This technique has a 97.95% accuracy rate when applied to the IDRID (Indian Diabetic Retinopathy Image Data set). In [7] CNN were consecutively applied to detect the MacTel2. The location of the retinal cavities was determined using manually annotated OCT images. In this study [8], DR images were categorized and DR lesions were located using a combination of CNN and YOLOv3. The evaluation yielded an accuracy of 89% using data sets from the 2019 Asia Pacific Tele-Ophthalmology Society (APTOS) and DDR fundus retina.

Nowadays most of the segmentation methods are based on the encoder-decoder network architecture like U-Net. Wang Y et al. [9] proposed a segmentation network for retinal blood vessel segmentation. Encoder layer, decoder layer, and softmax layer are all parts of the proposed SegNet architecture. The three data sets—DRIVE, STARE and HRF—are used to test and assess the suggested technique. CSU-Net [10] is a network that adopts the U-shaped model's structure with the encoder and a decoder. It consists of 2 channels—the spatial channel and the context channel—with an attention skip module and a feature fusion module. CSU-Net provides better performance in retinal vessel segmentation. CSU-Net performs better than other improved U-Nets in F1-score (0.825), Sensitivity (0.807), Specificity (0.978), Accuracy (0.956) and Area under the ROC Curve (AUC) (0.980) on DRIVE dataset, which indicates the effectiveness of this network. A multiscale connection encoder-decoder network that specializes in improved feature extraction is proposed in [11]. For low-resolution images, the multi-resolution fusion method allows direct participation in the final prediction while keeping all the semantic characteristics. This method achieves sensitivity of 0.9742 and an AUC of 0.9796, as well as accuracy of 0.9644 and sensitivity of 0.8730. Deep guidance network-based segmentation of the optic disc, cup, and vessels provided a guided filter to reduce the noise effect and preserve the edge information of the grey-scale guided image [12]. This segmentation model was experimented with common datasets like ORIGA, DRIVE, CHASEDB1 and REFUGE for retinal vessel segmentation, and optic disc and cup segmentation. Khan MA et al. [13] developed a novel method for retinal segmentation which uses an improved version of Laplacian of Gaussian detectors for edge detection. The normalized Gaussian Derivative Kernel in the second order is used in this model with an enhanced edge operator. The uniqueness of this proposed operator is that it can choose fine and large vessels with ease. The suggested method makes use of optimal normalization weights, enabling it to choose fine, small features from retinal images. Performance evaluation is done using the DRIVE, STARE, and CHASE DB1 databases, and reached a sensitivity of 0.785, a specificity of 0.967 and an accuracy of 0.952 on the DRIVE database, a sensitivity of 0.788, a specificity of 0.966 and a precision of 0.951 and a sensitivity of 0.787, a specificity of 0.968 and a precision of 0.952 on CHASE_DB1. The 3AU-NET model, which Jin L presented [14], is based on the fundamental U-Net design and uses threefold attention to get around the problems with the U-Net concept. On the DRIVE data set, the 3A-UNet model performed remarkably well, earning an ACC score of 0.9592, an AUC score of 0.9770, and a sensitivity score of 0.8537. Experimental findings have indicated that 3AU-Net may greatly boost the results of the segmentation of retinal blood vessels.

Optical Coherence Tomography Angiography (OCTA) is a non-invasive imaging technology that is increasingly being utilized to examine the retinal vasculature at the capillary level. Yuhui Ma et al. [15] presented OCTA-Net, a new split-based coarse-to-fine vessel segmentation network for OCTA pictures that can recognize thick and thin vessels individually. On the ROSE (Retinal OCT-Angiography vessel Segmentation) dataset, they thoroughly evaluate the state-of-the-art vessel segmentation models and the model OCTA-Net. The experimental results on the ROSE dataset demonstrate that this vascular segmentation strategy outperforms the current state-of-the-art methods. Fu Q et al. [16] set up a multi-scale convolution neural network with attention mechanisms to improve the accuracy and sensitivity of existing vascular segmentation algorithms (MSCNN-AM). This work proposes a supervised method for automatic retinal vessel segmentation based on CNN. The suggested technique is tested on three publicly available data sets: DRIVE, STARE, and CHASE DB1. The recommended method surpasses most current methods on DRIVE, STARE and CHASE DB1 individually, with a sensitivity of 0.8 342/0.8412/0.8132 and an accuracy of 0.9555/0.9658/0.9644. By introducing multi-scale feature extraction and attention-based methods, the proposed MSCNN-AM obtains better segmentation results and improves the model sensitivity.

Lam BS et al. [17] proposes a unique regularization-based multi-concavity method for accurately segmenting blood vessels in both pathological and normal retinas with bright and dark lesions. Numerous experimental findings using the STARE and DRIVE databases showed that the proposed technique performed better on both healthy and diseased retinas with an accuracy of 0.9567 on STARE and 0.9472 on DRIVE data sets. Park KB et al. [18] setup M-GAN, a novel conditional generative adversarial network that can segment the retina's blood vessels precisely and accurately by balancing losses over many deep, fully convolutional networks. They have also improved performance by doing fundamental pre-processing with the ACE algorithm and post-processing with the Lanczos resampling technique. They used the DRIVE, STARE, HRF, and CHASE DB1 datasets to validate the proposed technique. M-GAN generated an accuracy of 0.9876 on STARE data set, 0.9706 on DRIVE, 0.9736 on DB1 and 0.9761 on HRF data set. Khan TM et al. [19] method bridges the gap between semantic segmentation and medical image segmentation by framing the retinal vascular segmentation problem as a semantic pixel-wise segmentation task. The proposed scheme's performance is evaluated using three publicly accessible significant fundus image data sets. Based on image analysis in the DRIVE, CHASEDB1 and STARE data sets, the suggested technique achieves an accuracy of 0.978, 0.983 and 0.981 respectively. Because of the reduced computing complexity and memory overhead, as well as better segmentation efficiency, the suggested technique can be used in various automated diagnosis systems.

Zou B et al. [20] suggested a CNN architecture for multi-label classification for vessel segmentation. The DRIVE and STARE databases are used to assess the suggested technique. This technique gives an accuracy of .9519 and .9704 on DRIVE and STARE data sets, respectively. The red channel of the colored image was chosen after rescaling the image as part of the pre-processing stage of the proposed optic disc localization and segmentation approach [21]. For the segmentation of the optic disc, this method also employed fuzzy clustering, active contour, and Gaussian filtering techniques. This technique made use of the optic disc boundary's ground truths for the DIARETDB1, DRIVE, STARE and DRIONS. In all four databases, the approach had an average accuracy in the range of 97.01–99.46%. Jiang Y et al. [22] introduced recent advancements of segmentation network, multi path recurrent U-Net to segment the optic disc and cup of retinal images. The accuracy and dice values for segmenting an optic disc were 0.9967 and 0.9817, respectively, while for segmenting an optic cup, they were 0.8921 and 0.9950, respectively.

MultiResUNet [23] is a more effective U-Net design for medical image segmentation. In order to make feature maps more homogeneous, MultiResUNet provides some additional processing. It also creates a lightweight structure that requires less memory. A variety of visual modalities were used to test and assess the suggested strategy, including Fluorescence microscopy, Electron microscopy, Dermoscopy, Endoscopy and MR images. The performance of this architecture outperformed U-Net by 10.15 percent, 5.0 percent, 2.6 percent, 1.4 percent, and 0.6 percent, respectively. TM G et al. [24] utilized attention-based U-Net for segmentation of tumor. This model accomplished the ensemble by weighted averaging and showing promising results with an IOU score of 0.9591. Gharaibeh et al. [25] introduced the ST-MUNet algorithm, a brain image segmentation approach based on the Swin Transformer model combined with a modified U-Net and Generative Adversarial Network (GAN). The segmentation process was enhanced through the utilization of advanced filtering techniques, including the Hybrid Kuan Filter and Improved Frost Filter (HKIF) algorithm, during the preprocessing stage. Gao et al. [26] proposed a retinal vessel segmentation method that leveraged a dual-attention-based multiscale feature fusion residual network. By incorporating spatial attention and lightweight attention mechanisms, the model achieved significant improvements in segmentation performance. When evaluated on the DRIVE dataset, the model demonstrated an impressive accuracy of 0.9795. Yi et al. [27] presented a novel segmentation algorithm that utilizes a multiscale residual attention network to efficiently gather crucial information about blood vessels. The proposed approach exhibits a remarkable proficiency in capturing vessel bifurcations and vessel connections, leading to enhanced segmentation results. The model's capability to gather valuable insights across different scales contributes to its effectiveness in segmenting blood vessels more accurately.

3 METHODOLOGY

Multiple segmentation methods have been employed to identify retinal features in retinal images for detecting retinal diseases. In cases where segmentation is involved, combining the predicted segmentation masks from two distinct U-Net models can yield a more accurate segmentation mask. In this study, the segmentation of exudates, hemorrhages, microaneurysms, and blood vessels from retinal images is accomplished by fusing the segmentation masks generated by the MES-Net and U-Net models. The resulting model is referred to as MesU-Net, which builds upon the U-Net architecture and demonstrates enhancements over both the U-Net and MesNet models. The upcoming sections will elucidate the U-Net, MesNet, and the proposed MesU-Net model.

3.1 Segmentation using U-Net and MesNet architecture

U-Net architecture in Figure 6 is the main segmentation network for image segmentation task. This network consists of expansion and contraction parts. Because it contains four down and up-sampling layers connected by skip connections, it performs well in multiple biomedical image segmentation.

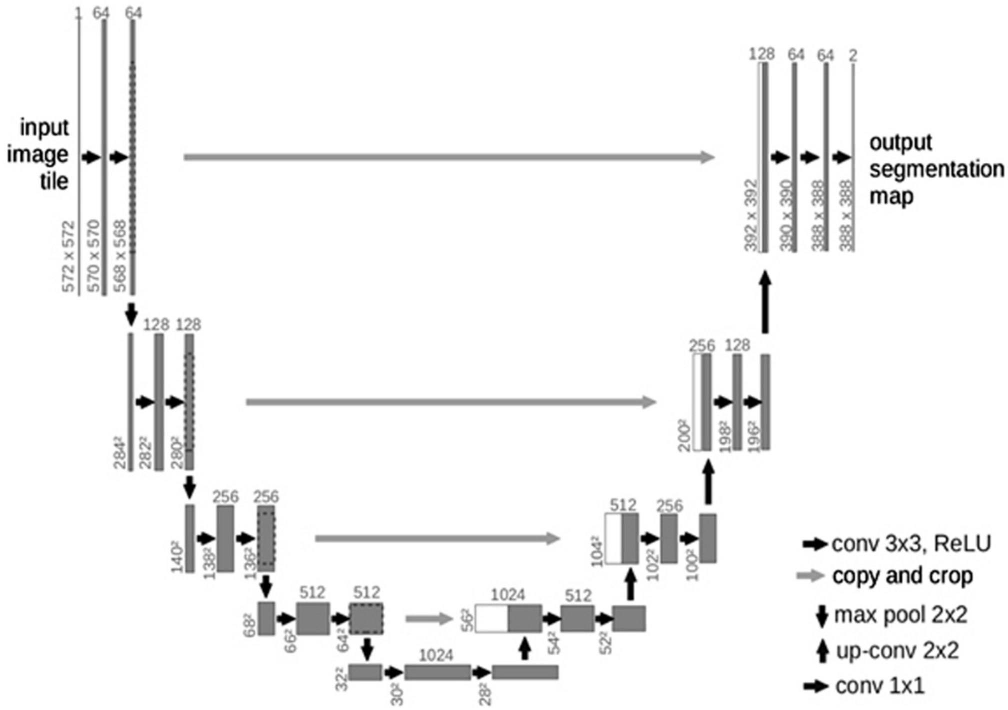


Fig. 6. U-Net architecture

MesNet is a Convolution Neural Network [28] that adopts the basic structure of the U-Net model and is used for semantic segmentation. MesNet uses U-Net as its main support structure and modifies the U-Net by adding additional three blocks: Multi-scale Feature Pre-extraction (MFP), Encoder Spatial Cascading Encoding (ESCE), and decoder input Squeeze-and-Excitation network (SE) block, which is presented in Figure 7. In order to deliver the results of an image more quickly, MesNet can be used in clinical situations. The MFP (Multi-scale Feature Pre-extraction) block is developed to extract the multi-scale characteristics from the input image of any resolution. By utilizing the MFP Block, the network's performance can be enhanced. The ESCE (Encoder Spatial Cascading Encoding) path increases the network's ability to extract semantic features and the rate at which features are reused. Combining the encoder path and the MFP block output in MesNet architecture enables extensive semantic characteristic extraction at various scales. The SE (Squeeze-and-Excitation network) block, a channel attention method in MesNet can reduce the semantic gaps between the encoder and decoder path. It has the potential to close semantic gaps between encoder and decoder paths, resulting in improved segmentation performance. The result obtained from the SE Block is concatenated with the decoder path to produce better segmentation results. The segmentation results produced by this method are precise.

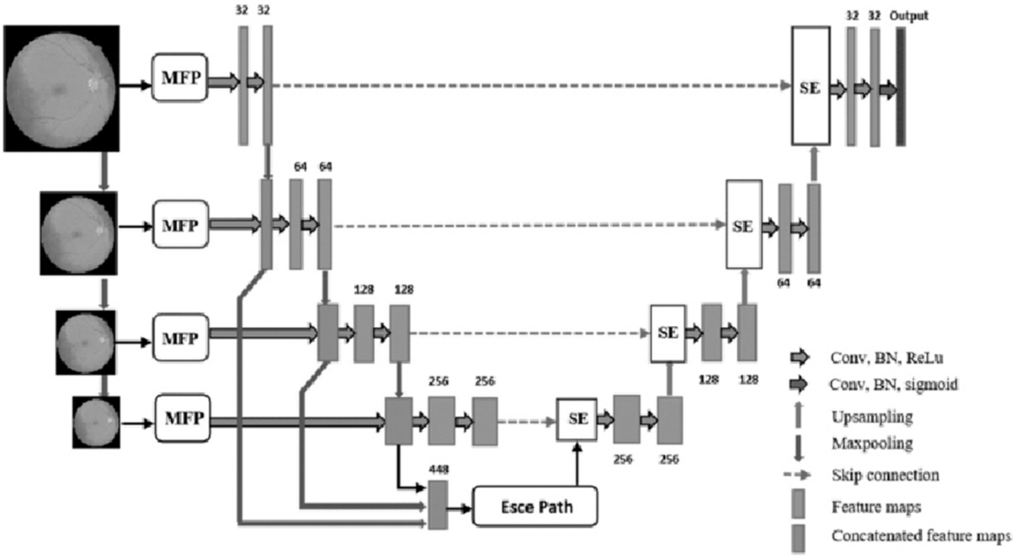


Fig. 7. The overall framework of MesNet [28]

3.2 MesU-Net

Segmentation models using U-Net and MesNet provide less segmentation accuracy. The U-Net design may have restrictions on the contextual information utilized for segmentation. The U-Net along with the Mes-Net improves the performance of the model making it suitable for medical image segmentation with high clinical application. The improved segmentation model is efficient enough to segment low-resolution images and to segment images with insufficient capillary contrast in the extraction of retinal blood vessels. Therefore, the MesU-Net can be applied to a variety of medical image segmentation tasks with exceptional clinical application abilities and can contribute to the expansion of computer-aided diagnosis technology as well. Concatenated versions of the MesNet and U-Net models make up the proposed model, called MesU-Net, shown in Figure 8. This method proposes the MesU-Net, a revolutionary segmentation network, which could effectively segment the exudates, microaneurysms, hemorrhages and blood vessels present in the given retinal sample. Extraction of features from the input image is the sole purpose of the multi-scale feature pre-extraction block in the first part of the model. The MFP block continuously samples the source image at four distinct resolutions, creating images from which semantic information is extracted. The encoder route is concatenated with the relevant feature maps acquired by the MFP block for multi-scale input images. As a result, the semantic properties of various scales and receptive fields may be thoroughly retrieved, and the network's segmentation performance can be considerably enhanced. We first continually down-sample the original images to create four different resolution images, then extract semantic features from these images using the MFP module. The acquired feature maps are then combined in U-Net with the input feature maps of the matching encoder layer. Because of its high performance, the atrous convolution is commonly employed in current deep learning semantic segmentation problems.

The second U-Net model receives the MesNet results as input, resulting in the modified MesU-Net model. The U-Net (II) takes the output of the MesNet as its input and down-samples along the encoder path. Skip connections are present in the model that allows deeper extraction of semantic features and can also alleviate gradient disappearance. A second U-Net was used by the MesU-Net to improve the experimental results, and it provides the single channel output. This model created the ESCE route to let the original encoder extract deep context features by cascading semantic features from distinct encoder regions. The skip connections of the MesNet are concatenated with the skip connections of the second U-Net (U-Net II) and are connected to the same level decoder path. The last layer is subjected to 3 × 3 convolution and sigmoid activation, and generates a single channel output of the segmented retinal image. The loss function used in this model is a combination of cross-entropy and dice coefficient.

Segmentation of exudates, hemorrhages and microaneurysms was performed separately from the retinal vessel segmentation. From the dataset, images were picked for training and validation. To enhance the performance of the model and prevent overfitting, these images were enhanced using horizontal flipping, vertical flipping, Gaussian noise, and grid distortion. The ADAM method was used to optimize the network.

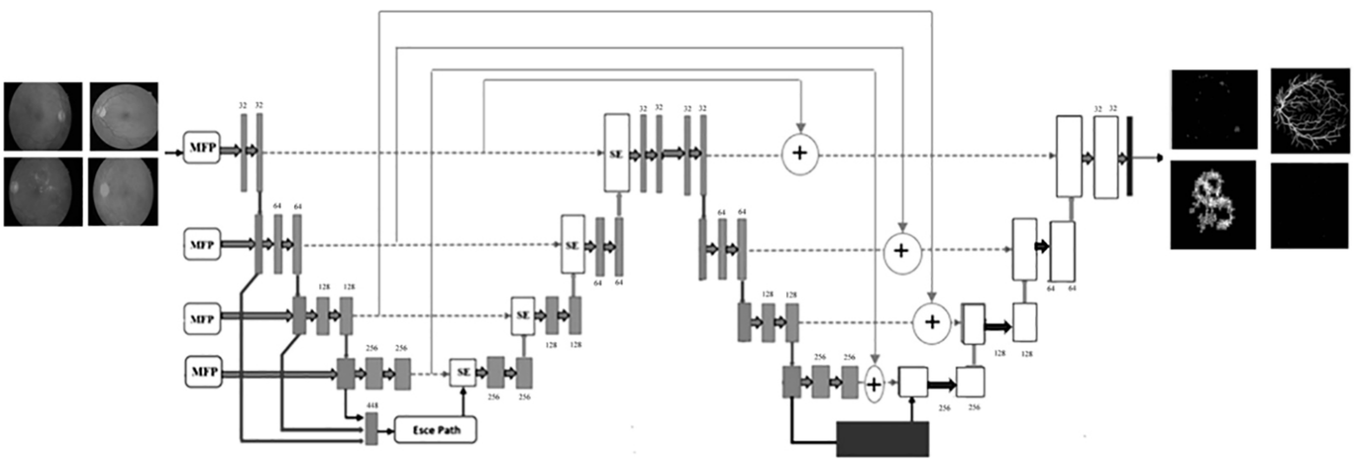


Fig. 8. Proposed segmentation network MesU-Net

4 RESULTS AND DISCUSSIONS

Segmentation of exudates, hemorrhages and microaneurysms was done using the Indian Diabetic Retinopathy Image Dataset (IDRID). This dataset was utilized in this work of segmenting retinal images. The IDRID is the first database in the world with images of diabetic retinopathy. It includes pixel-level annotations of common diabetic retinopathy abnormalities and healthy retinal elements. The IDRID dataset contains clinically marked ground truth to perform segmentation of the exudates, micro aneurysms and hemorrhages. The dataset includes 81 color retinal samples and its segmented ground-truth. All images are 4288 × 2848 pixels in size. DRIVE data set was used to evaluate the performance of the retinal vessel segmentation of the model proposed. The DRIVE dataset consists 40 color retinal images with the size of 584 × 565. The DRIVE dataset was developed to enable comparative studies on the segmentation of blood vessels in retinal images. This dataset was used in analyzing the segmentation performance of our proposed model. At the pixel level, common faults in diabetic retinopathy and common retinal components are identified. Each image in the collection includes information on the extent of diabetic retinopathy. This makes it perfect for the development and testing of image analysis algorithms for the early diagnosis of diabetic retinopathy. Eighty-one color retinal samples and segmented ground truth are included in the data set. Here the results of the MesU-Net are closer to the given ground truth, hence it segments the results accurately.

The segmentation result in Figure 9a–d contains the original image and the segmented result of exudates, hemorrhage, microaneurysms and blood vessels. The performance of the retinal vascular segmentation of the suggested model is assessed using the DRIVE data set. Forty retinal images in color, each measuring 584 × 565 pixels, make up the DRIVE data set.

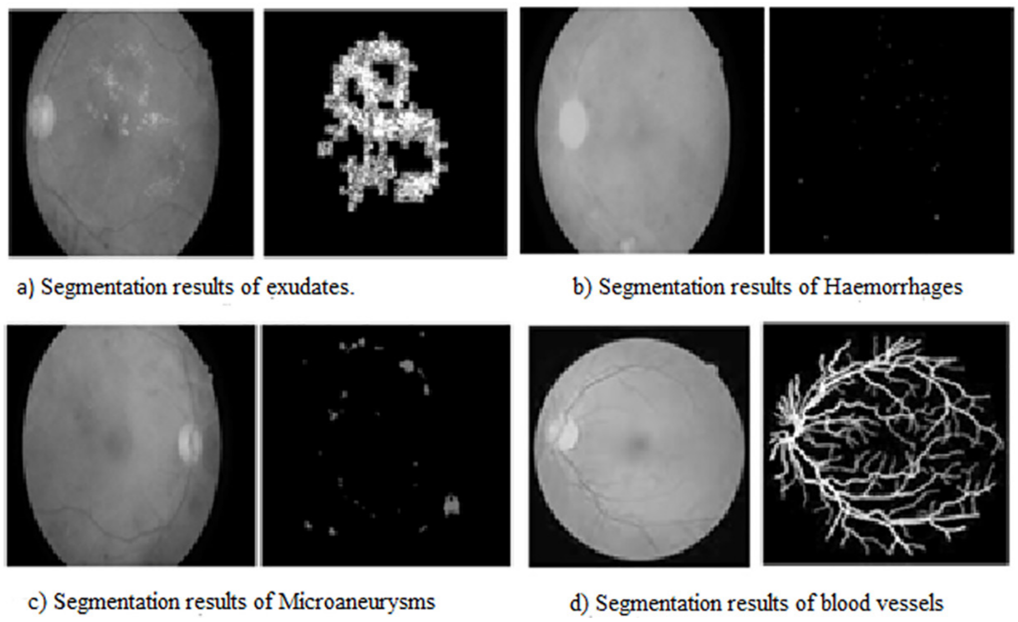
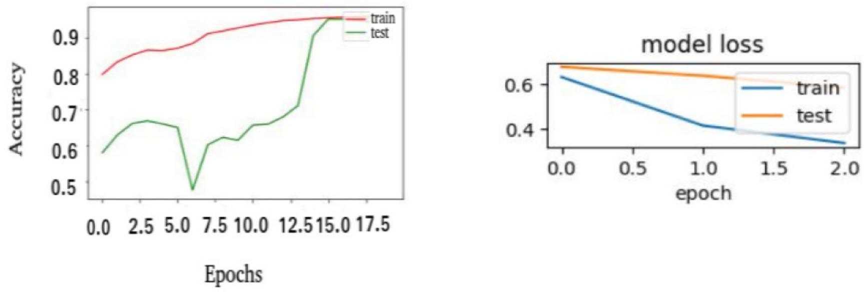
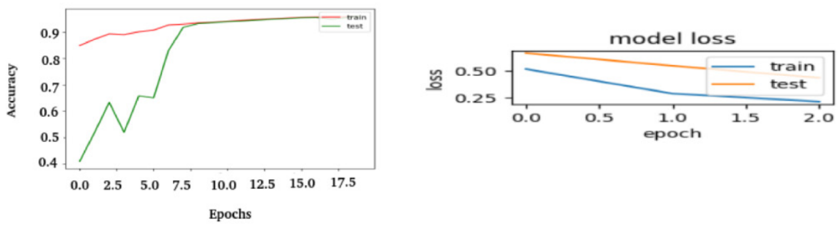


Fig. 9. The segmentation result of retinal features using MesU-Net

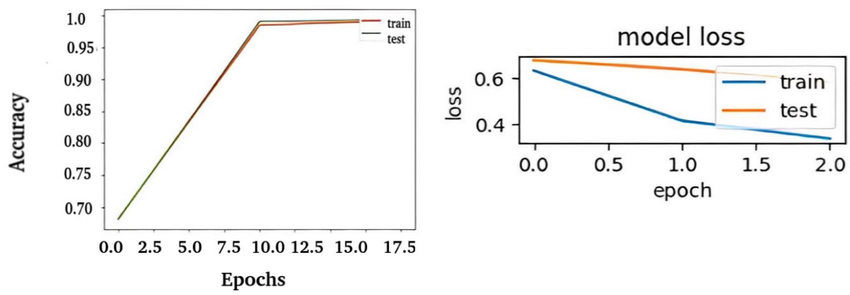
The segmentation results obtained through U-Net show some data loss and incomplete segmentation in certain areas. When using the MesU-Net model, it successfully replicates the blood vessel's support structure and can segment the thin vessels into an acceptable number of visually appealing outputs. Hence, by using MesU-Net, a huge collection of shapes can be captured and also provides detailed information about the thin vessels. The proposed model MesU-Net can be effectively used to segment retinal vessels and can produce segmentation results of the image with various data sources.



a) Accuracy and loss of exudates



b) Accuracy and loss of hemorrhages



c) Accuracy and loss of micro aneurysms

Fig. 10. Training and testing accuracy of retinal features using MesU-Net

Segmentation results using MesU-Net are more in line with the provided ground truth. U-Net, MesNet, and MesU-Net models were used to compare the retinal vessel's performance. The evaluation outcomes utilizing the aforementioned techniques are displayed in Table 1. The MesU-Net has a segmentation accuracy of 97.6% for exudates, 98.1% for hemorrhage and 99.2 for microaneurysm and an accuracy of 83.0% for segmenting retinal vessels. These findings conclude that the suggested model MesU-Net has the potential to solve the given medical segmentation challenges. Training and testing accuracy of segmentation of exudates, hemorrhages and micro aneurysms using MesU-Net and its loss is depicted in Figure 10a–c.

Table 1. Performance analysis of proposed model with other models

Segmentation Type	Model	Accuracy	Loss
Exudate Segmentation	U-Net	0.911	0.228
	MesNet	0.956	0.961
	MesU-Net	0.976	0.149
Blood Vessel Segmentation	U-Net	0.759	0.615
	MesNet	0.773	0.867
	MesU-Net	0.837	0.437
Hemorrhage Segmentation	U-Net	0.926	0.236
	MesNet	0.959	0.963
	MesU-Net	0.981	0.434
Segmentation of Microaneurysm	U-Net	0.947	0.274
	MesNet	0.936	0.961
	MesU-Net	0.992	0.586

Accurately segmenting tiny micro aneurysms in the retinal images is challenging for the segmentation models that have been proposed. The challenging aspect of the proposed model lies in the scarcity of labeled data available for training. This problem can be solved by enhancing the dataset using a variety of augmentation approaches. The performance comparison of MesU-Net with other segmentation methods are provided in Figure 11.

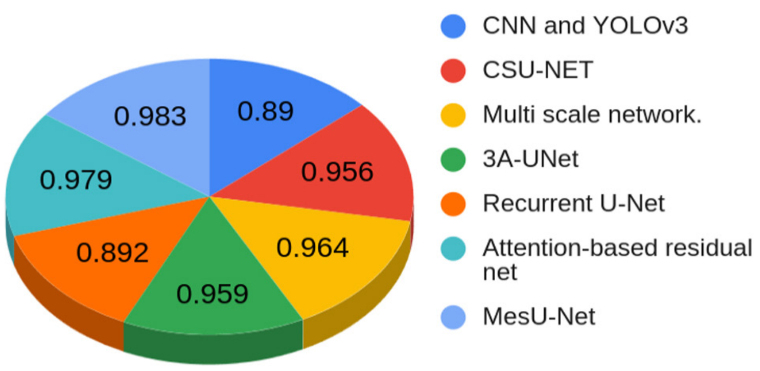


Fig. 11. Performance comparison of MesU-Net with other segmentation methods

5 CONCLUSION AND FUTURE SCOPE

This paper provides a detailed analysis of U-Net and MesNet segmentation networks. We have developed a novel network called MesU-Net, which can be applied to a variety of medical segmentation tasks. This model combines U-Net and MesNet, making it ideal for retinal image segmentation with broad clinical applications. The segmentation of retinal blood vessels from low-resolution images and images with insufficient capillary contrast becomes possible with this improved ensemble approach. To facilitate more comprehensive semantic feature extraction, the U-Net model incorporates a series of encoding and decoding layers, as well as a skip connection that combines the skip connections of MesNet and U-Net. The proposed method's accuracy for the segmentation of exudates, hemorrhages, microaneurysms, and blood vessels is 97.6%, 98.1%, 99.2%, and 83.7%, respectively. It produces better results when compared to U-Net and MesNet in various aspects. The proposed method can be utilized in future studies to extract retinal features linked to various retinal illnesses from a broader collection of annotated images using different imaging modalities. The segmentation process's performance can be enhanced through the utilization of GAN-based augmentation during the preprocessing stage.

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