JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Feature Optimization Based Retinal Vessel Segmentation Using Deep Learning Algorithm

Muskan Tembhare
Student
Department of CSE
NIIST Bhopal

Prof. Mahendra Sahare
Associate Professor
Department of CSE
NIIST Bhopal

Prof. Anurag Srivastava M-tech
Head of Department
Department of CSE
NIIST Bhopal

Abstract

Retinal blood vessel segmentation and analysis is critical for the computer-aided diagnosis of different diseases such as diabetic retinopathy. This study presents an automated deep learning method for segmenting the retinal vasculature based on optimized methods. The algorithm initially applies a preprocessing step using morphological operators to enhance the vessel tree structure against a non-uniform image background. The main pro-cessing applies the adaptive histogram equalization, followed by vessel validation, vessel refinement and vessel reconstruction to achieve the final segmentation. The method was tested on three publicly available datasets. Segmentation performance was evaluated using three measures: accuracy, receiver operating characteristic (ROC) analysis, and the structural similarity index. ROC analysis resulted in area under curve values of 97.39%, 97.01%, and 97.12%, for the DRIVE, , respectively. Also, the results of accuracy were 0.9688, 0.9646, and 0.9475 for the same datasets.

Keywords: - Retinal Blood, Segmentation, Deep Learning, CNN Introduction

The morphological transformation of the retinal vascular system is closely linked to various ophthalmological and cardiovascular diseases, such as glaucoma, hypertension, diabetes, and arteriosclerosis. Consequently, the morphology of retinal vessels is a crucial evaluation standard for many diseases[1,2,3]. Retinal blood vessels can be visualized through color fundus images, allowing clinicians to diagnose, screen, treat, and evaluate diseases by analyzing these images[4]. However, automatic methods are highly desired, as the current manual labeling of retinal blood vessels requires professional expertise and significant manpower. Automatic segmentation and centerline extraction of retinal blood vessels remain challenging due to the small size of the vessels, overlapping branches, distortion, severe stenosis, and varying image quality caused by low contrast, noise, and artifacts. Retinal vessel segmentation encounters significant challenges in feature extraction and feature optimization. Effective feature optimization is essential for improving the segmentation performance of retinal fundus images. Recently[5,6], numerous researchers have proposed various approaches for extracting feature components such as texture features, color features, and boundary features from fundus images. However, the extraction process often results in the loss of some core features, which can diminish segmentation performance. Feature optimization aims to reduce redundant features in fundus images, thereby enhancing segmentation accuracy. Several approaches have been employed for feature optimization, including swarm intelligence-based algorithms like particle swarm optimization, genetic algorithms, and glowworm optimization algorithms. These methods help to refine the extracted features, ensuring that essential information is preserved and redundancy is minimized, leading to better segmentation outcomes[7,8]. Most deep neural networks, including U-net, require a large amount of high-quality labelled data for training. However, there are very few fundus image datasets with extensive pixel-level labels, and the quality of these labels can vary significantly. Producing high-quality annotations demands a lot of time from many experts, making it costly and time-consuming

. To address this issue, self-supervised learning from unlabelled data has garnered significant interest. However, the complex distribution of retinal capillaries in fundus images, along with the significant variation in the size, thickness, and orientation of retinal vessels between patients, degrades the accuracy of existing self-supervised learning-based segmentation methods when applied to retinal vessels. In this work, we propose a deep learning-based method for blood vessel segmentation. Our approach involves enlarging the kernel size of the convolutional layer to cover vessel pixels and their neighbouring areas more effectively for feature extraction. The main contribution lies in experimentally identifying the optimal kernel size in correlation with retinal image resolution. Within this framework, we introduce a novel U-net extension that applies convolution layers parameterized by the identified kernel size. The proposed architecture is trained and tested on retinal sub-image datasets, with the resulting segmented patches being merged to generate the final vessel segmentation map. The rest of paper organised as in section II related works, in section III proposed methodology, in section IV experimental analysis, and finally conclude in section V.

II. Related work

In recent reported survey, significant effort has been dedicated to developing automated methods for retinal vessel segmentation. However, several challenges remain, including the presence of central vessel reflex, lesions, and low contrast, which require further research. A robust deep learning approach to retinal vessel segmentation must address these issues. One of the primary challenges with current CNN-based models is their substantial computational complexity due to millions of trainable parameters. Author [1] suggests a computational method for retinal vascular segmentation that involves pre-processing and image enhancement, followed by two improvement steps based on filtering and histogram comparison. With a 92% normality rate, this approach is found to be superior to others. Author [2] highlights that the proposed method is well-suited for point-of-care screening platforms due to its lightweight nature and high segmentation accuracy. Author [3] presents an unsupervised method for segmenting arteries in retinal images, achieving average processing times of less than 3.17 seconds per image and reporting sensitivity, specificity, and accuracy scores of 0.7271, 0.9798, and 0.9573 on the DRIVE database, and 0.7164, 0.9760, and 0.9560 on the STARE database. Author [4] demonstrates through experimental validation on three datasets that their pipeline outperforms state-of-the-art methods, particularly in sensitivity, which is crucial for detecting small vessels. Author [5] shows that their approach achieves similar segmentation accuracy with less labelled data. For instance, without needing any labelled ground-truth images, they matched the accuracy of typical supervised learning methods on the DRIVE and Vampire datasets, achieving an accuracy of 0.96 on the DRIVE dataset after thorough training. Author [6] reports that their GT-DLA-dsHFF method outperforms existing techniques, with in-depth discussions confirming the effectiveness of the proposed three modules. Author [7] proposes a novel deep learning architecture for retinal vascular segmentation that involves increasing the convolution layer's kernel size to capture more neighbouring and vessel pixels for feature extraction. Author [8] uses the Anam-Net

model, a lightweight CNN with bottleneck layers in the encoder and decoder stages, to segment retinal vessels with high accuracy and low computational costs. Author [9] conducts experiment on four publicly available retinal vascular datasets, demonstrating the effectiveness of their approach, and integrates their network into an IoT framework to assist medical diagnostics. Author [10] indicates that the convergence and error performance of each method are comparable, with statistical studies highlighting the stability and robustness of each metaheuristic strategy for distinguishing between background and vascular pixels in retinal images. Author [11] finds that their architecture, created using the proposed method, delivers greater performance with less than 1% of the original U-Net parameters compared to other state-of-the-art models. Author [12] emphasizes the importance of using the U-Net architecture and extensive data augmentation to resolve input image issues and improve performance. Author [13] shows that their algorithm segments small blood vessels more effectively than most existing methods, achieving sensitivity metrics of 0.8745, 0.8903, and 0.8916 on three datasets, which is nearly 0.1 higher than other current methods. Author [14] suggests that their network's strong multi-scale representation capabilities allow for detailed information extraction, showing significant promise for clinical retinal vascular segmentation applications due to its notable performance and computational efficiency. Author [15] illustrates the value of combining semantic segmentation modules with fundamental medical image segmentation techniques in their deep learning-based architecture for retinal vascular segmentation. Author [16] creates a 3D-to-2D retinal vascular segmentation system using a Progressive Attention-Enhanced Network (PAENet), comprising two primary components: a two-dimensional segmentation path and a three-

dimensional feature-learning path. Author
[17] utilizes a CNN and CLAHE to address retinal blood vessel segmentation, with experimental evaluations showing that their approach outperforms state-of-the-art methods, achieving an accuracy of 0.9806. Author [18] states that their method provides greater topological continuity and superior segmentation and centreline extraction outcomes compared to state-of-the-art approaches at different sizes. Author [19] introduces GSAU-Net, based on a gated skip-connection network with adaptive up-sampling, achieving vessel segmentation F-measures of 83.13%, 81.40%, and 84.84% on the DRIVE, CHASE, and STARE datasets, respectively. Author [20] describes a method involving vessel validation, refinement, and reconstruction processes following the primary processing with the Radon transform applied to overlapping windows to obtain the final segmentation.

III. Proposed Methodology

This section describes proposed methodology for retinal vessel segmentation based on feature optimization and deep learning. First, construct a training model utilizing blood vessel and background data. Then, employ this training model to classify each pixel in retinal images. A common approach for this is blood vessel segmentation using convolutional neural networks (CNNs). Figure 1 depict proposed model of blood vessel segmentation based on convolutional neural network. The proposed model operates in three phases: 1he initial step involves preprocessing the input retinal image to prepare it for further analysis. This may include operations such as noise reduction, normalization, and contrast enhancement to improve image quality. In this phase, specific channel components of the image are extracted, with a particular focus on the green channel. The green channel is often preferred in retinal image analysis because it provides the best contrast for blood vessels compared to the red and blue channels. Following the extraction of the green channel, adaptive histogram equalization (AHE) is applied. This technique enhances the contrast of the image
by adjusting the intensity distribution of the pixels, making it easier to distinguish blood vessels from the background. The pre-processed image is then fed into a convolutional neural network (CNN) for training. The CNN is trained to differentiate between vessel and non-vessel pixels. Once trained, the CNN model segments the retinal image by classifying each pixel as either a blood vessel pixel or a non-vessel pixel. Through these phases, the model effectively preprocesses the retinal images, enhances relevant features, and accurately segments blood vessels using the trained CNN.

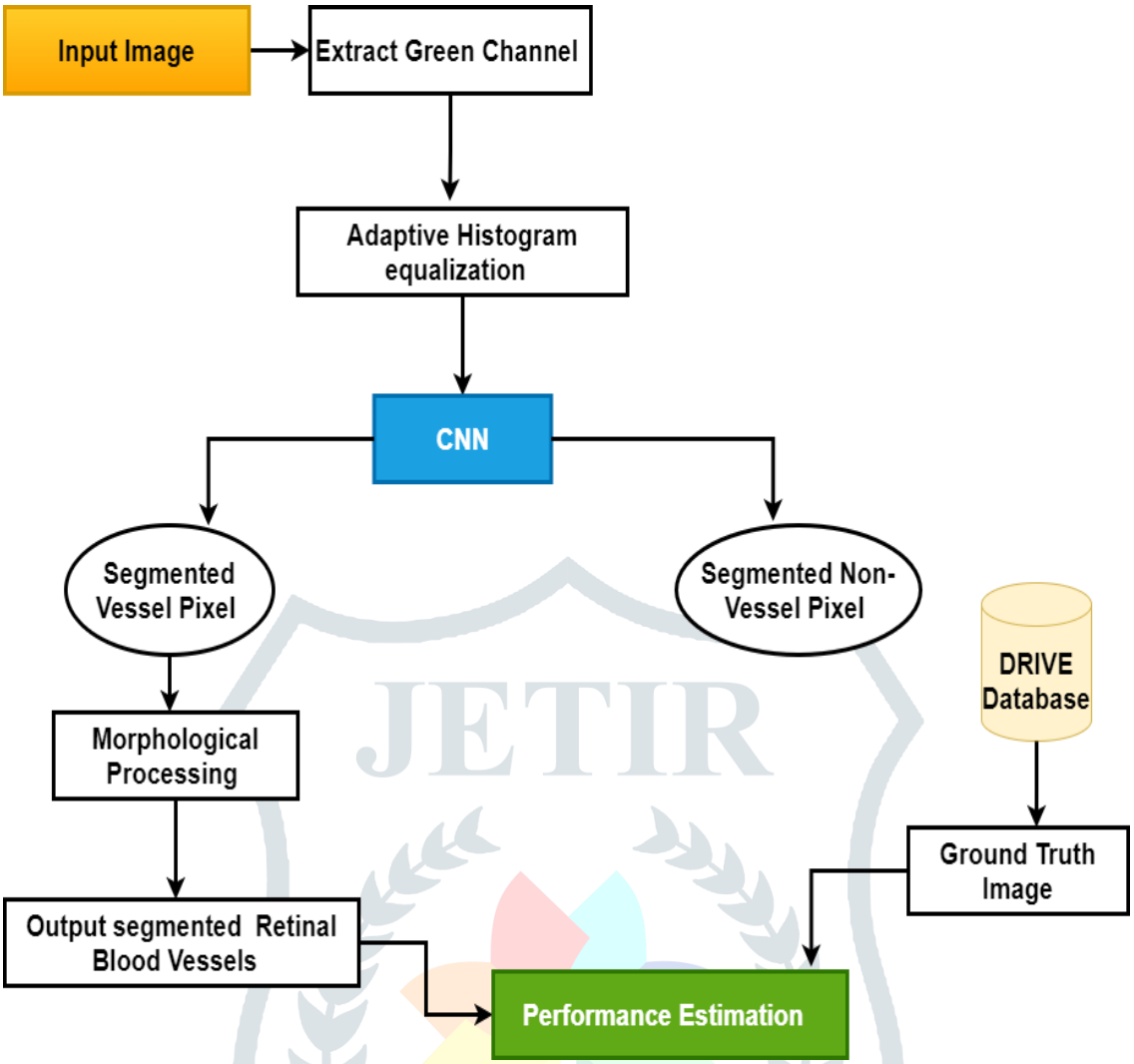

Figure 1 proposed model of Retinal blood vessels Segmentation Algorithm for blood vessel segmentation

Input:

- Retinal images (I)
- Labels (ground truth segmentations) (L') Output:

-Segmented image with blood vessels identified (S)

Define the CNN architecture, typically consisting of:

- Input layer: Takes in the pre-processed image.
- Convolutional layers: Apply multiple filters to extract features.
- Activation layers: Use non-linear activations (e.g., ReLU).
- Pooling layers: Down sample the feature maps to reduce dimensionality.
- Fully connected layers: Combine the features for classification.
- Output layer: Use a SoftMax or sigmoid function to classify each pixel.

Initialize the CNN model parameters (weights and biases).

Define the loss function (e.g., binary cross-entropy) and the optimizer (e.g., Adam or SGD). Train the CNN model using the training set:

- Forward pass: Compute the output of the CNN for the input images.
- Loss computation: Calculate the loss between the predicted segmentation and the ground truth labels.
- Backward pass: Perform backpropagation to compute the gradients.
- Parameter update: Update the model parameters using the optimizer.

Validate the model on the validation set and tune hyperparameters if necessary.

Evaluate the trained CNN model on the test set using appropriate metrics (e.g., accuracy, precision, recall, F1-score).

IV. Experimental Analysis

To evaluate the performance of proposed algorithm for blood vessels segmentation uses MATLAB2014R software. The proposed algorithm evaluates on reputed open-access dataset like, DRIVE. The DRIVE dataset consists of 40 fundus images having a resolution of 565 X584 pixels obtained for the DR screening program. The set of 40 images has been divided into two sets a training set and a test sets, each with 20 images. The output of our proposed algorithm is a probability prediction map that indicates the likelihood that a given pixel is either a vessel or not. For each of the three datasets, we threshold a probability map with a value of 0.4 to produce the binary segmentation of retinal vessels. A blood vessel pixel is one whose predicted value on the probability map exceeds the threshold; otherwise, it is regarded as a background pixel. We applied the well-known, standard evaluation metrics for deep learning models in the segmentation and analysis of medical images. By comparing our developed algorithm for the segmentation of retinal vessels to the publicly available ground truth from experts, we hope to assess its performance. The abbreviations TP, FP, TN, and FN stand for true positive, false positive, true negative, and false negative, respectively. The metrics for evaluation are SN, specificity (SP), and ACC.

$$Sensitivity = \frac{Total\ TP}{Total\ TP + Total\ FN} \quad \ldots\ldots (1)$$

$$Specificity = \frac{Total\ TN}{Total\ TN + Total\ FP} \quad \ldots\ldots (2)$$

$$Accuracy = \frac{Total\ TP + Total\ TN}{Total\ TP + Total\ FP + Total\ TN + Total\ FN} \quad \ldots\ldots (3)$$

$$AUC = \frac{sensitivity + specificity}{2} \quad \ldots\ldots (4)$$

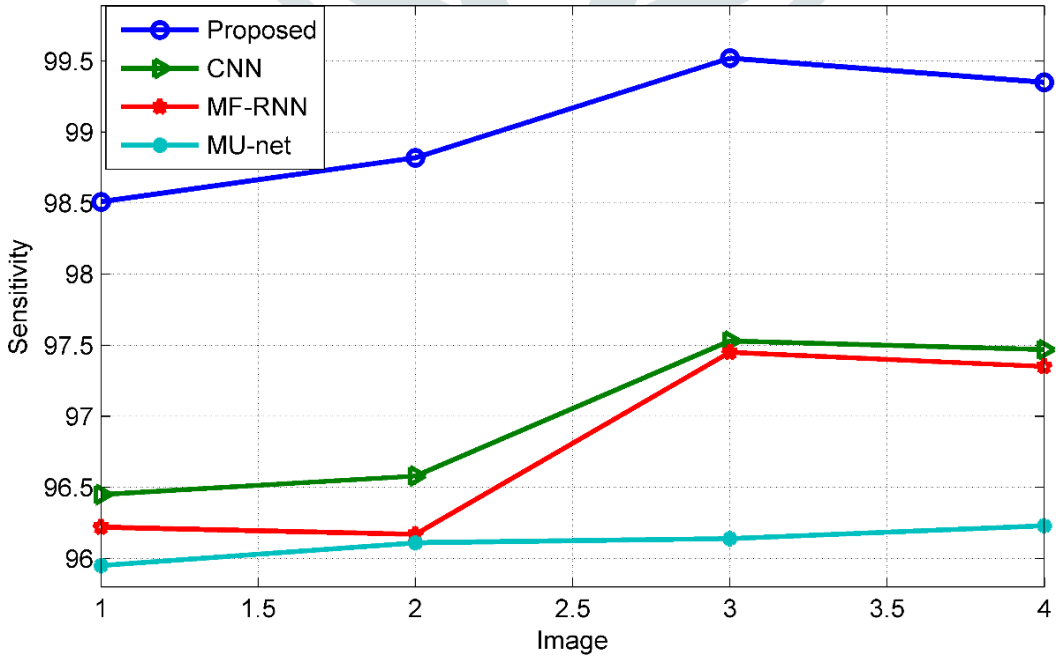

Figure: 2 Comparative result analysis of sensitivity of DRIVE Image employed proposed method, CNN, MF-RNN and MU-net.

Figure (2) depicts that the value of proposed is better than the other three methods, in which the value of proposed is displayed as 99.52 which is a better performance, while the value of CNN is 97.53. And the MF-RNN value is 97.45, which is better, and the MU- net value is also performing better, which is 96.23.

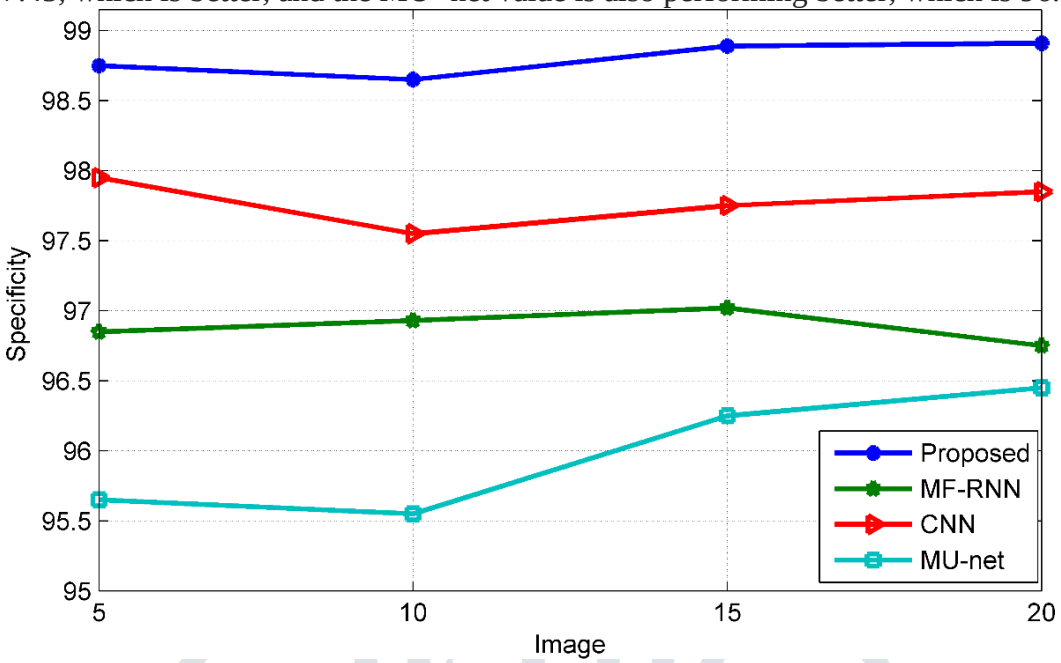

Figure: 3 Comparative result analysis of specificity of DRIVE Image employed proposed method, CNN, MF-RNN and MU-net.

Figure (3) depicts that the value of proposed is better than the other three methods, in which the value of proposed is performed as follows: 98.91 which is a better performance, while the value of CNN is 97.95. And the value of MF-RNN is 97.02, which is better, and the value of MU- net is also performing better, which is 96.45.

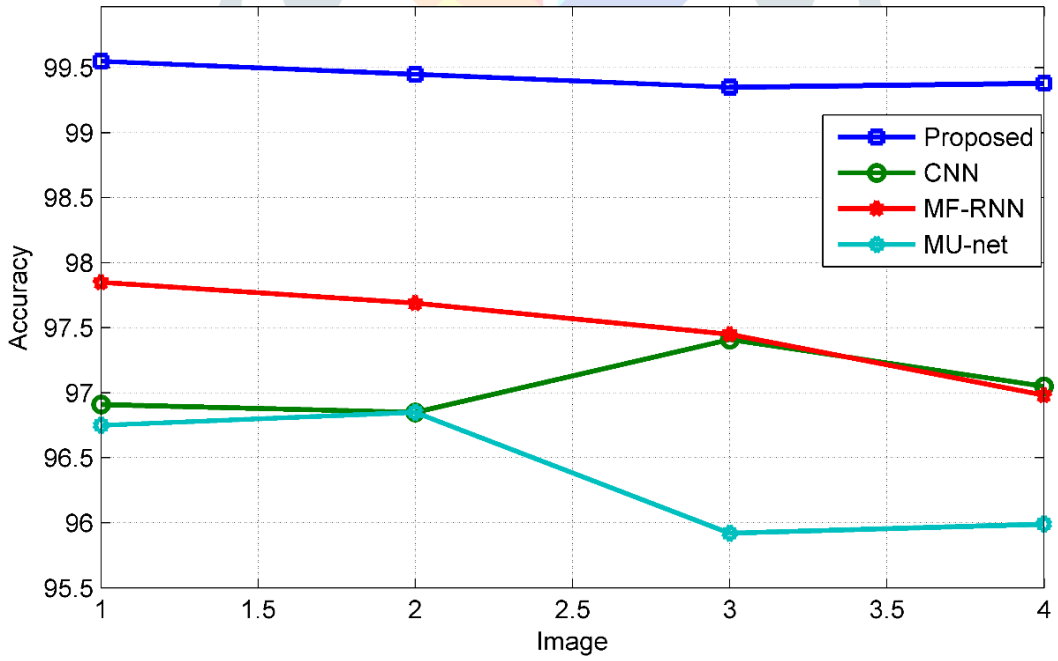

Figure: 4 Comparative result analysis of accuracy of DRIVE Image employed proposed method, CNN, MF-RNN and MU-net.

Figure (4) depicts that the value of proposed is better than the other three methods, in which the value of proposed is performed as follows: 99.55 which is a better performance, while the value of CNN is 97.41 And the value of MF-RNN is 97.85, which is better, and the value of MU-net is also performing better, which is 96.85.

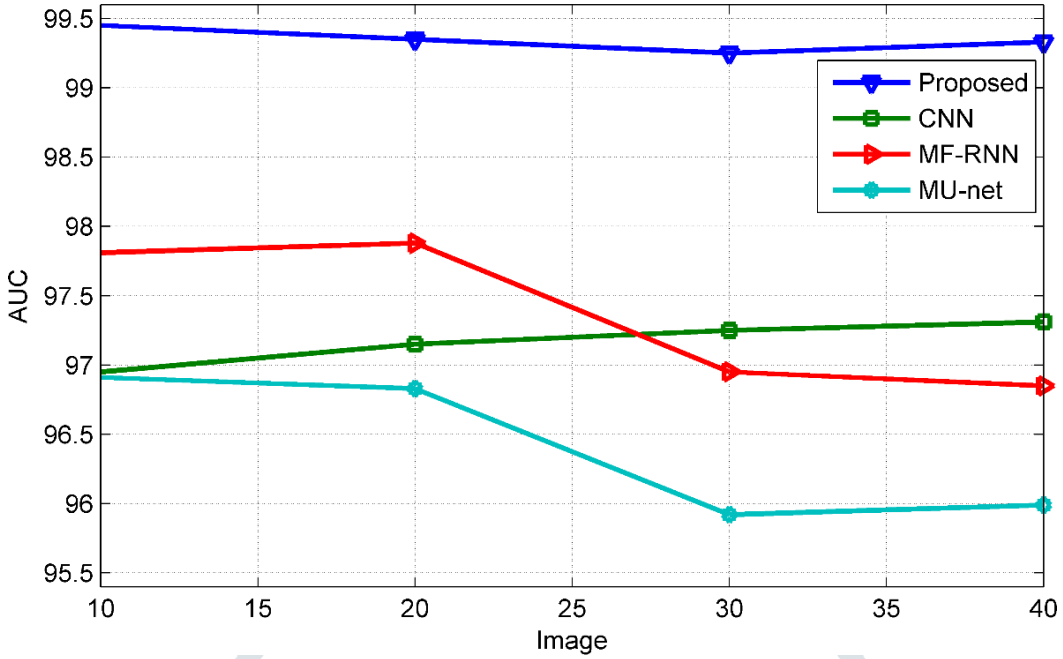

Figure: 5 Comparative result analysis of AUC of DRIVE Image employed proposed method, CNN, MF-RNN and MU-net.

Figure (5) depicts that the value of proposed is better than the other three methods, in which the value of proposed is performed as follows: 99.45 which is a better performance, while the value of CNN is 97.31 And the value of MF-RNN is 97.88, which is better, and the value of MU-net is also performing better, which is 96.91.

V. Conclusion & Future work

In this paper, we propose a model for automatic retinal vessel segmentation. Our model incorporates histogram equalization to enhance the preprocessing stage of channel extraction. In the extension path of the CNN, fully connected (FC) layers are utilized to facilitate the flow of information from the encoder to the decoder, effectively reducing noise and enabling the decoder to focus on processing relevant boundary-related information. To address the challenge of recovering fine details, adaptive up sampling is employed, which captures the correlation information between feature maps and improves the recovery performance of small vessels. The feature maps are then scaled to the same size as the input image to achieve pixelwise prediction. Our method was validated on the DRIVE dataset, and experimental results demonstrated that our approach outperforms existing methods, including CNN [14], MF-RNN [18], and MU-Net [39], in retinal vessel segmentation.

References

[1] Rehman, Amjad, Majid Harouni, Mohsen Karimi, Tanzila Saba, Saeed Ali Bahaj, and Mazar Javed Awan. "Microscopic retinal blood vessels detection and segmentation

using support vector machine and K-nearest neighbors." Microscopy research and technique 85, no. 5 (2022): 1899-1914.

[2] Haider, Syed Irtaza, Khursheed Aurangzeb, and Musaed Alhussein. "Modified Anam-Net Based Lightweight Deep Learning Model for Retinal Vessel Segmentation." Computers, Materials & Continua 73, no. 1 (2022).

[3] Muzammil, Nayab, Syed Ayaz Ali Shah, Aamir Shahzad, Muhammad Amir Khan, and Rania M. Ghoniem. "Multifilters-based unsupervised method for retinal blood vessel segmentation." Applied Sciences 12, no. 13 (2022): 6393.

[4] Karaali, Ali, Rozenn Dahyot, and Donal J. Sexton. "DR-VNet: retinal vessel segmentation via dense residual UNet." In International Conference on Pattern Recognition and Artificial Intelligence, pp. 198-210. Cham: Springer International Publishing, 2022.

[5] Tu, Zhonghao, Qian Zhou, Hua Zou, and Xuedong Zhang. "A Multi-Task Dense Network with Self-Supervised Learning for Retinal Vessel Segmentation." Electronics 11, no. 21 (2022): 3538.

[6] Li, Yang, Yue Zhang, Jing-Yu Liu, Kang Wang, Kai Zhang, Gen-Sheng Zhang, Xiao-Feng Liao, and Guang Yang. "Global transformer and dual local attention network via deep-shallow hierarchical feature

fusion for retinal vessel segmentation." IEEE Transactions on Cybernetics (2022).
[7] Boudegga, Henda, Yaroub Elloumi, Rostom Kachouri, Asma Ben Abdallah, and Mohamed Hedi Bedoui. "Extended U-net for retinal vessel segmentation." In International Conference on Computational Collective Intelligence, pp. 564-576. Cham: Springer International Publishing, 2022.
[8] Aurangzeb, Khursheed, Syed Irtaza Haider, and Musaed Alhussein. "Retinal vessel segmentation based on the anam-net model." Elektronika ir Elektrotechnika 28, no. 3 (2022): 54-64.
[9] Shi, Cao, Canhui Xu, Jianfei He, Yinong Chen, Yuanzhi Cheng, Qi Yang, and Haitao Qiu. "Graph-based convolution feature aggregation for retinal vessel segmentation." Simulation Modelling Practice and Theory 121 (2022): 102653.
[10] Çetinkaya, Mehmet Bahadır, and Hakan Duran. "Performance comparison of most recently proposed evolutionary, swarm intelligence, and physics-based metaheuristic algorithms for retinal vessel segmentation." Mathematical Problems in Engineering 2022 (2022): 1-25.
[11] Wei, Jiahong, Guijie Zhu, Zhun Fan, Jinchao Liu, Yibiao Rong, Jiajie Mo, Wenji Li, and Xinjian Chen. "Genetic U-Net: automatically designed deep networks for retinal vessel segmentation using a genetic algorithm." IEEE Transactions on Medical Imaging 41, no. 2 (2021): 292-307.
[12] Uysal, Enes Sadi, M. Şafak Bilici, B. Selin Zaza, M. Yiğit Özgenç, and Onur Boyar. "Exploring the limits of data augmentation for retinal vessel segmentation." arXiv preprint arXiv:2105.09365 (2021).
[13] Ma, Yuliang, Zhenbin Zhu, Zhekang Dong, Tao Shen, Mingxu Sun, and Wanzeng Kong. "Multichannel retinal blood vessel segmentation based on the combination of matched filter and U-Net network." BioMed research international 2021 (2021): 1-18.
[14] Zhou, Yukun, Zailiang Chen, Hailan Shen, Xianxian Zheng, Rongchang Zhao, and Xuanchu Duan. "A refined equilibrium generative adversarial network for retinal vessel segmentation." Neurocomputing 437 (2021): 118-130.
[15] Sun, Muyi, Kaiqi Li, Xingqun Qi, Hao Dang, and Guanhong Zhang. "Contextual information enhanced convolutional neural networks for retinal vessel segmentation in color fundus images." Journal of Visual Communication and Image Representation 77 (2021): 103134.
[16] Wu, Zhuojie, Zijian Wang, Wenxuan Zou, Fan Ji, Hao Dang, Wanting Zhou, and Muyi Sun. "PAENet: A progressive attention-enhanced network for 3D to 2D retinal vessel segmentation." In 2021 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), pp. 1579-1584. IEEE, 2021.
[17] Yadav, Arun Kumar, Arti Jain, Jorge Luis Morato, and Divakar Yadav. "Retinal Blood Vessel Segmentation using Convolutional Neural Networks." In KDIR, pp. 292-298. 2021.
[18] Pan, Lin, Zhen Zhang, Shaohua Zheng, and Liqin Huang. "MSC-net: multitask learning network for retinal vessel segmentation and centerline extraction." Applied Sciences 12, no. 1 (2021): 403.
[19] Jiang, Yun, Huixia Yao, Shengxin Tao, and Jing Liang. "Gated skip-connection network with adaptive upsampling for retinal vessel segmentation." Sensors 21, no. 18 (2021): 6177.
[20] Tavakoli, Meysam, Alireza Mehdizadeh, Reza Pourreza Shahri, and Jamshid Dehmeshki. "Unsupervised automated retinal vessel segmentation based on Radon line detector and morphological reconstruction." IET Image Processing 15, no. 7 (2021): 1484-1498.