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Retinal Blood Vessel Segmentation Approach Based on Multi-Feature Optimization Using Deep Learning Algorithm

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Abstract: Retinal vessel segmentation aids ophthalmologists in diagnosing issues by revealing the vascular features in fundus images, facilitating the examination of the retina's intricate structures. Diseases such as glaucoma, age-related macular degeneration, and diabetic retinopathy are linked to morphological abnormalities in retinal blood vessels. In this study, we propose a three-stage technique for assessing the impact of retinal blood vessel segmentation. The method involves a preprocessing module, followed by double thresholds and morphological image reconstruction techniques to produce a segmented image of the vessels. The performance of the proposed method was validated using the publicly available DRIVE database, achieving sensitivity values of 0.911 and 0.921, which surpass other existing methods. Additionally, it achieved accuracy values of 0.961 and 0.954 on the STARE and DRIVE databases, respectively, comparable to other methods. This new method for retinal blood vessel segmentation can assist medical experts in diagnosing eye diseases and recommending timely treatments.

Keywords*: Retinal Segmentation, DR, Feature Optimization, Deep Learning CNN*

Introduction

The retinal vessels play a crucial role in the body's blood circulation. Changes in the shape and size of human body organs and tissues can indicate health status. Observing the retinal vasculature helps doctors track and diagnose fundus diseases such as diabetic retinopathy (DR). Therefore, being able to visually observe the distribution and detailed information of the retinal vasculature is essential for accurate diagnoses. However, the structure of the retinal vasculature is highly complex, with high curvature and diverse shapes, and the difference between vessel areas and the background is often subtle. Additionally, fundus images are easily affected by uneven illumination and noise, presenting significant challenges for retinal vessel segmentation. The incremental advancements in computer technology and intelligent segmentation of retinal vessels have become a significant research area, supporting the diagnosis and decision-making in ophthalmic diseases. The application of deep learning algorithms in image segmentation has greatly improved the accuracy of blood vessel segmentation. Deep learning provides both time-dependent and time-independent algorithms for feature extraction and optimization. Since they became widely used, neural network models have produced important findings. A fully convolutional neural network model (FCNN) for intraretinal image segmentation in optical coherence tomography (OCT) images was proposed [7]. Their experimental results demonstrated that the model achieved good results despite its simplicity [7,8] proposed a deep fully convolutional network stacking multiple generative adversarial networks [9] (M-GAN) and pre-processed retinal vessel images using automatic colour equalisation (ACE). A multichannel pooling block was incorporated amidst the stack layers of the M-GAN model in order to account for fluctuations at distinct length scales.[10] retinopathy diagnosis was made with a fusion neural network. This makes it necessary for some research to combine datasets that were gathered using various cameras and settings [4]. The large variation in retinal blood vessel thickness is another significant obstacle. Therefore, both thick and thin vessel segmentation should be achievable with the current retinal vessel extraction techniques. The fact that each patient's retinal characteristics are unique presents another difficulty. Lastly, it's possible for other retinal structures, such as the DR lesions, Fovea, and Optic Disc, to be mistakenly identified as retinal blood vessels. Therefore, we propose a Pix2Pix GAN model in this work, which can successfully navigate all of these obstacles and effectively segment retinal blood vessels on a variety of datasets, such as the ARIA, DRIVE, and HRF datasets. Figure 1 shows an example of manually extracted retinal vasculature from a DRIVE dataset image.

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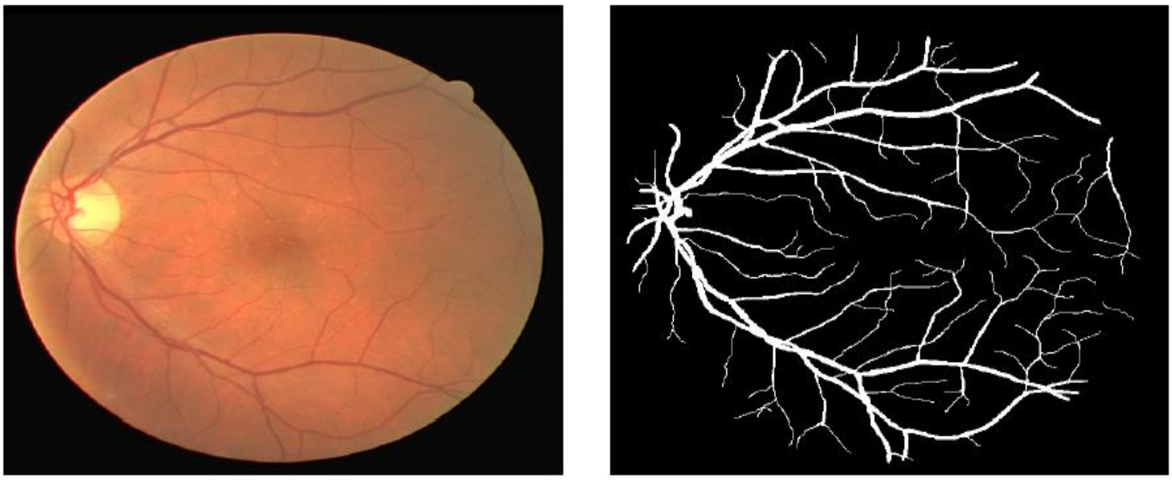

Fig 1 Retinal vasculature segmentation sample [12]

The segmentation approach using multiple features consists of analysing various parts of fundus images to enhance the accuracy and reliability of retinal vessel segmentation. This method leverages both the inner and outer edges of the images to extract comprehensive features that contribute to a more detailed and precise segmentation process. Inner-side features often include detailed textures that characterize the retinal vessels. Techniques like Gabor filters and wavelet transforms are used to capture these textures, which help differentiate vessels from the background. Analysing the intensity gradients within the retinal images helps identify the vessels' central lines and their variations in brightness, aiding in the accurate detection of vessel structures. Outer-side features focus on the boundaries of the retinal vessels. Edge detection algorithms such as Canny or Sobel are employed to highlight the vessel edges, providing clear demarcations between vessels and the surrounding tissue. This involves examining the geometric properties of the vessels, such as their curvature and branching patterns, which are crucial for distinguishing vessels from other anatomical features in the fundus image. CNNs are adept at creating feature maps that represent different aspects of the fundus images, such as textures and edges. By stacking multiple convolutional layers, CNNs can capture complex patterns and hierarchical features. To ensure consistency across different images, normalization techniques are applied to standardize the intensity values, which helps in mitigating variations due to lighting conditions and image acquisition settings. Augmenting the dataset with variations such as rotations, flips, and contrast adjustments increases the model's ability to generalize, improving its performance on diverse fundus images. The rest of paper organized as in section II related works, in section III methodology of segmentation, in section IV experimental Analysis, in section V results and discussion and finally conclude paper in section VI.

II. Related work

Recently several survey report studies in retinal vessel segmentation were employed image processing, optimization algorithm and deep learning models. The employed deep learning models significantly enhance the performance of segmentation approach. In [1], the impact of vessel contrast on retinal blood vessel segmentation was evaluated. A novel technique for retinal vessel segmentation using coherence enhancement was proposed. The challenges of small vessel analysis impact sensitivity and algorithm robustness. Challenging images often contain noise, contrast variations, and illumination issues. In [2], retinal vessel segmentation techniques based on two-dimensional color images were examined. Segmentation approaches were classified into eight major categories. Central light reflection can cause segmentation gaps, leading to variations. Small vessels with poor contrast are often missed during the segmentation process. Imaging artifacts like blurs and noise complicate the segmentation process, and lesions can generate false positives, disrupting blood vessel identification. In [3], the LEA U-Net was introduced to enhance retinal vessel segmentation with local features and attention mechanisms. Small features are often lost in the U-Net transmission process due to its structure. There are challenges in processing methods for small, complex vessel structures, and the uneven distribution of retinal blood vessels affects feature extraction. In [4], the Grasshopper Optimization algorithm was combined with fuzzy edge detection for retinal blood vessel segmentation. No specific funding or conflicts of interest were reported, and no limitations were mentioned. In [5], a method for enhancing retinal images for blood vessel extraction with high accuracy was proposed. The WKFCM-DBF method achieved high sensitivity, specificity, and accuracy. A complete pre-processing method for retinal blood vessel extraction was developed.

Annotated data collection is challenging due to the expertise and cost required. Low-quality retinal images hinder robust feature representation in deep learning models, and class imbalance affects network performance due to fewer positive examples. In [6], a U-Net-based model for accurate retinal vessel segmentation was proposed, using ResNest to minimize information loss in retinal vascular features. Effectiveness was demonstrated through comparative and ablation experiments. U-Net feature loss occurs due to the encoder convolution layer operation, and mismatches in contextual information processing occur due to the skip connection. Challenges in retinal vessel segmentation arise due to image characteristics. In [7], fuzzy-based thresholding for retinal vessel segmentation was explored. Membership functions were adapted for hard thresholding approaches. Conventional thresholding may lose vessel pixels, affecting retinal disease analysis, and thresholding techniques may fail near threshold values in vessel segmentation. In [8], multi-resolution feature extraction was used for spatial information preservation. A systematic assessment of design choices was conducted for improved retinal vessel segmentation. Adversarial learning was employed for foreground segmentation enhancement with fewer parameters. In [9], a method for post-processing deep learning segmentations was developed, ensuring the connected structure of retinal vessels. Approaches for preserving structural integrity in retinal vessel segmentation were presented, with limitations discussed in Section 5. The DVAE method was not utilized due to vessel thickness widening. In [10], the MS-LSDNet network for vessel segmentation was proposed, featuring geometric skeleton reconnection. An adaptive hysteresis threshold method for vascular extraction was introduced. A vascular tree structure reconstruction algorithm based on geometric skeletons was developed. Challenges include maintaining vascular structural connectivity in retinal blood vessel segmentation, with interruptions in thin blood vessel regions with low confidence. In [11], the ASDC method for RV and FAZ segmentation in OCTA images was introduced. This method reduces computational cost and time for OCTA image analysis. Multi-scale vessel complexity, inhomogeneous image quality, and non-perfusion challenge segmentation. Encoder-decoder inefficiency during the down-sampling phase affects feature loss. There is a lack of standard datasets with high-quality FAZ and RV annotations. In [12], the OCE-Net for retinal vessel segmentation was proposed, capturing orientation and context. Gabor convolution encodes a single orientation, limiting complex vessel features. Existing convolutions lack orientation consideration, affecting vessel continuity. In [13], deep learning was shown to accelerate DR classification proficiency for precise recognition of severity. Image processing aids in designing plausible treatment plans for diabetic retinopathy. Segmented vessels are less useful in deep learning analysis. There is no comparison with segmented drusen for diabetic retinopathy diagnosis. In [14], the MSR U-Net model for retinal blood vessel segmentation was introduced, replacing the convolution block and skip connections with the MSR convolution block. Better performance was achieved in segmenting blood vessels of varying thicknesses. Limited generalization of vessels is due to complex morphology and lesion confusion. Inadequate contextual information challenges vessel segmentation accuracy. Small training datasets from benchmark datasets DRIVE, STARE, and CHASEDB1 are a limitation. In [15], five neural network architectures for retinal vessel segmentation were evaluated, achieving segmentation accuracy up to 98% using a custom dataset. Lower-quality OCT fundus images suffer from noise and resolution issues. There is difficulty in selecting the best reconstruction method for neural networks. Fragmentation issues with thin vasculature occur due to low resolution. In [16], the Cross-Fusion Channel Attention module enhances channel features for retinal vessels. The Additive Attention Gate module improves spatial features. The soft pool pooling method reduces information loss during down-sampling. Existing methods face challenges due to complex retinal vessel structures. The proposed algorithm enhances channel features and spatial information for segmentation accuracy. In [17], the DOADL-BVSC model for DR grading with deep learning was introduced. No specific limitations were mentioned in the research paper. In [18], a model that outperformed U-Net, ResUNet, U-Net3+, ResUNet++, and CaraNet was proposed. A residual module was introduced for enhanced feature extraction in retinal vessel segmentation. Full-scale skip connections were integrated for combining different scales of feature maps. No specific limitations were mentioned in the provided contexts. In [19], a model that improves convergence, flexibility, robustness, and feature refinement was proposed. State-of-the-art performance in retinal vessel segmentation was achieved. Convergence steps and parameters were reduced compared to the baseline U-Net. Difficulty in distinguishing thin vessels from backgrounds affects segmentation accuracy. The small number of samples in databases makes segmentation challenging. In [20], a convolutional auto-encoder model for retinal vessel segmentation was proposed, addressing the importance of automated vessel segmentation for early disease detection. High specificity in segmentation was achieved with competitive performance on public datasets. Manual segmentation presents challenges due to diverse eye vessel structures. Manual segmentation in fundus images is time-consuming. In [21], segmentation using K-means optimized by particle swarm optimization (PSO) was explored. Gabor filters were utilized for texture analysis in retinal blood vessel segmentation. Thresholding has a long computation time. K-means is constrained by the initial centroid, leading to a local optimum. In [22], an improved vessel segment extraction method using the Six Sigma process was proposed. Concerns on skeletonization and vessel segment extraction novelty were addressed. No external funding was received for this research, and the data availability statement is not applicable. In [23], depth-wise separable convolutions were introduced to reduce computational complexity. A novel encoder-decoder model for retinal vessel segmentation was proposed. A feature fusion residual module was used for effective feature fusion. Data imbalance due to the uneven distribution of blood vessels was noted. Incomplete topology is captured by certain feature fusion modules. In [24], a deep learning-based approach using U-net was a major contribution. Retinal vessels change with age, and there is no fixed structure or pattern. Thin branching vessels are hard to detect accurately. In [25], a new Coye algorithm amendment for retinal vessel extraction was proposed, investigating curvelet coefficient modification for vessel edge and curvature enhancement. No specific limitations were mentioned in the paper. In [26], major blood vessel and minor vessel segmentation with enhanced accuracy was examined. Few methods focus on minor vessel classification, lacking discriminative features. Limited knowledge leads to the misclassification of minor vessels as background. In [27], an automated deep learning procedure for feature extraction from retinal images was introduced. Integration of advanced image segmentation techniques was conducted for precise retinal segmentation. Traditional methods lack complexity for early DR categorization. Individual models underperform compared to ensemble approaches in DR detection. In [28], the Pix2Pix GAN model for retinal vasculature segmentation on datasets was introduced, achieving good results on ARIA, DRIVE, and HRF datasets. Limitations include smaller datasets for retinal vasculature extraction and the availability of few ophthalmologists for manual retinal screening. In [29], a flattening transformation for data labeling and specialized data augmentation was proposed. A hybrid U-net for reference segmentation performance on the dataset was introduced. Integration of vesselness measures boosts segmentation performance. Dependence on clear 3D retinal layer segmentation for 2D images is a limitation. There is an overestimation of vessel diameter in the z-axis and underestimation in the x-axis. In [30], authentic hospital images were used for segmentation, not web-based datasets. Image augmentation and noise removal techniques were implemented for high accuracy. Existing works used web images, not authentic hospital patient images. The proposed model focuses on noise removal, not disintegration and reconstruction. Incorporating 2D images is a drawback, with future aims directed toward 3D images.

III. Methodology

This section describes a novel methodology for retinal vessel segmentation that utilizes feature optimization within a deep learning framework. The proposed algorithm aims to enhance the accuracy and robustness of retinal vessel segmentation by leveraging multi-feature extraction and optimization. The model architecture, as illustrated in Figure 2, consists of an encoder with three main stages. Each stage is designed to progressively extract and refine features, producing detailed feature maps that highlight the retinal blood vessels. The encoder is structured into three main stages, each responsible for different levels of feature extraction. These stages work in a hierarchical manner, capturing increasingly complex features of the retinal vessels. The initial stage involves multiple convolutional layers that apply filters to the input image, capturing basic features such as edges and textures. This helps in identifying the initial points of the blood vessels. Non-linear activation functions like ReLU are applied to introduce non-linearity, enabling the network to learn more complex patterns. Pooling operations, such as max pooling, are used to down sample the feature maps, reducing their spatial dimensions while retaining important information. This stage helps in focusing on the most relevant features and discarding noise. To prevent the vanishing gradient problem and maintain feature integrity, residual connections may be used. These connections allow the network to retain information from earlier layers, enhancing the feature extraction process. In the final stage, deeper convolutional layers are applied to further refine the feature maps. These layers capture high-level features, such as the intricate branching patterns and curvatures of the blood vessels. Attention mechanisms can be integrated to focus on the most significant features, ensuring that small and complex vessel structures are accurately detected. At each main stage of the encoder, the network outputs feature maps that represent different aspects of the blood vessels. These feature maps are essential for capturing the multi-feature points of the retinal vessels, providing a comprehensive representation of their structure. The extracted features from all stages are combined and optimized to produce a detailed segmentation map. This combination allows the model to leverage information from different levels of abstraction, improving the overall segmentation accuracy. This loss function is used to handle class imbalance by focusing on the overlap between the predicted and ground truth vessel regions. This function helps in fine-tuning the segmentation boundaries, ensuring precise detection of vessel edges. Dropout layers are used to prevent overfitting by randomly deactivating a fraction of neurons during training. Batch normalization is applied to standardize the inputs of each layer, improving training stability and convergence speed.

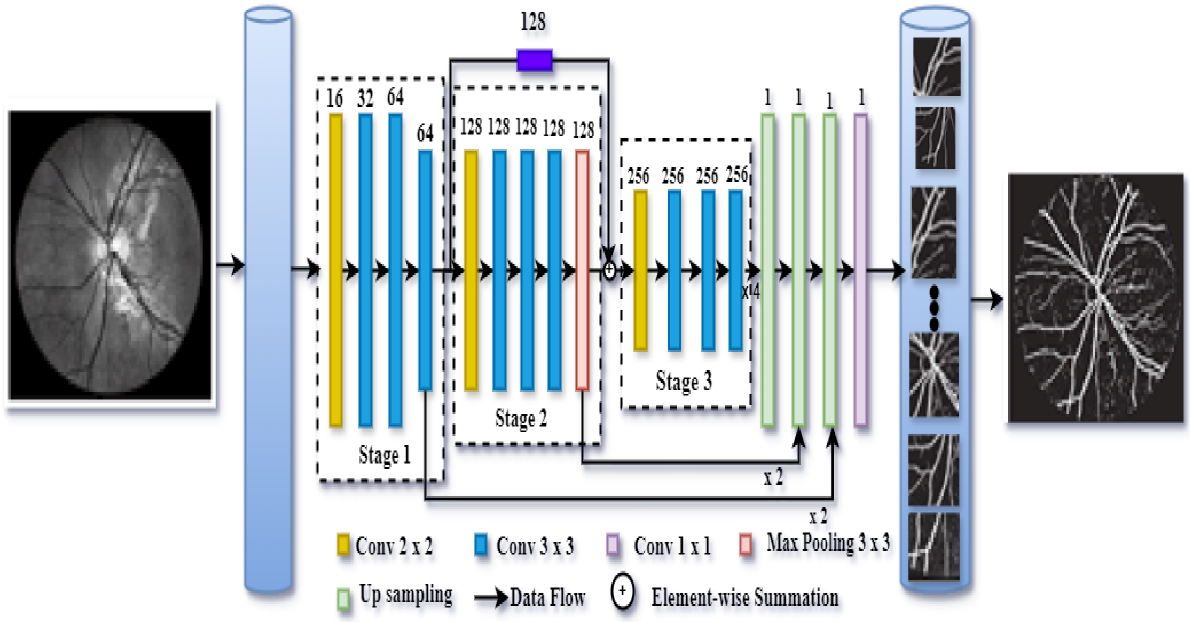

Fig 2 proposed model of retinal vessel segmentation

Algorithm for deep learning

Begin

Set of Feature vector FV1=(T1, CNN)

Set of feature Vector FV22=(T2, CNN)

C= Binary entropy of Loss

Mapping of Feature Vectors ={FV1,FV2,FV3}

End

Were

1. T0 is class of data space for the processing of vector
2. T1 is training level of class for the process of learning factor
3. T2 is final class of prediction of stock price

Process of ReLu

Begin

M =mapped model of Loss from class

New D=Φ

For each prediction $=(x, y) \in D'$(D' is trained sample of data)

For j= 1 to final T

Segmentation ={ x,C2 class of M: map of final_s}

newT =newT (errors)

return Segmentation

end

IV. Experimental Analysis

To evaluate the performance of proposed algorithm for blood vessels segmentation uses MATLAB2018R software. The proposed algorithm evaluates on two reputed open-access datasets like, DRIVE. The DRIVE dataset consists of 40 fundus images having a resolution of 565 X584 pixels obtained for the DR screening program. 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.

$$Sensitivity = \frac{Total\ TP}{Total\ TP + Total\ FN}$$

$$Specificity = \frac{Total\ TN}{Total\ TN + Total\ FP}$$

$$Accuracy = \frac{Total\ TP\ + Total\ TN}{Total\ TP + Total\ FP + Total\ TN + Total\ FN}$$

$$AUC = \frac{sensitivity\ + specificity}{2}$$

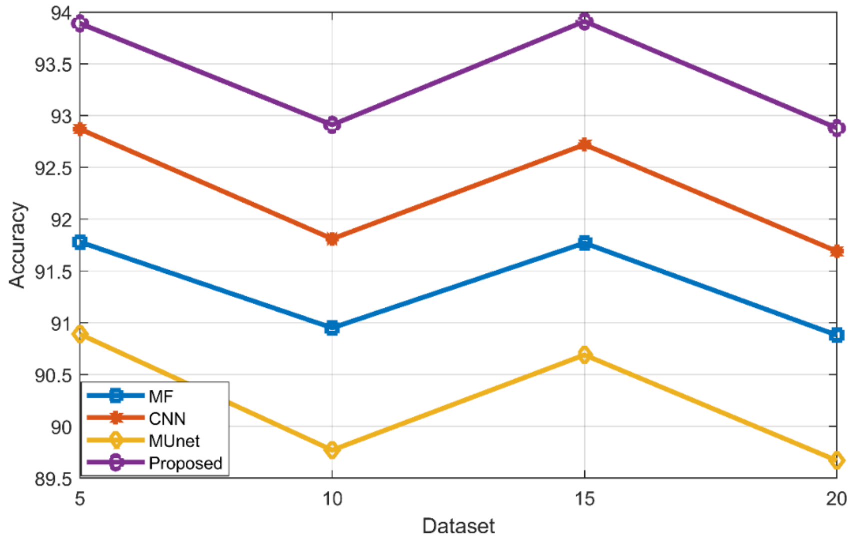

Fig 3 Comparative performance of Accuracy of Proposed, CNN, MF, and MU-net method using DRIVE dataset.

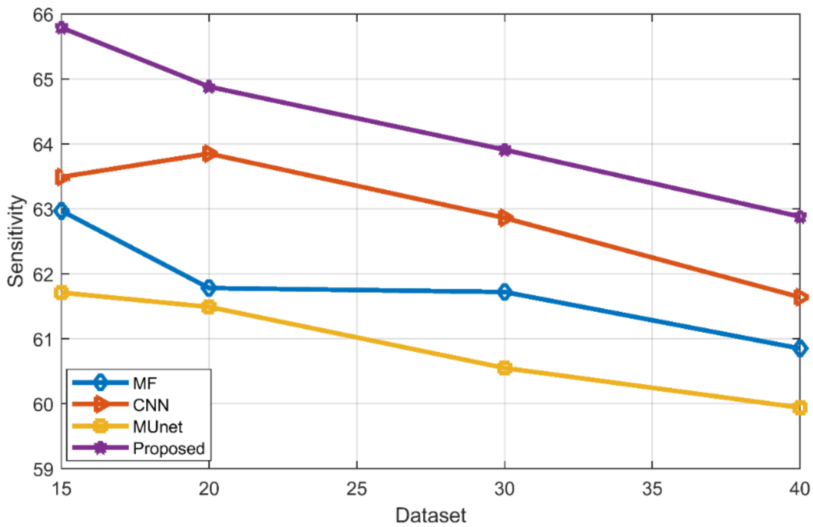

Fig 4 Comparative performance of sensitivity of Proposed, CNN, MF, and MU-net method using DRIVE dataset.

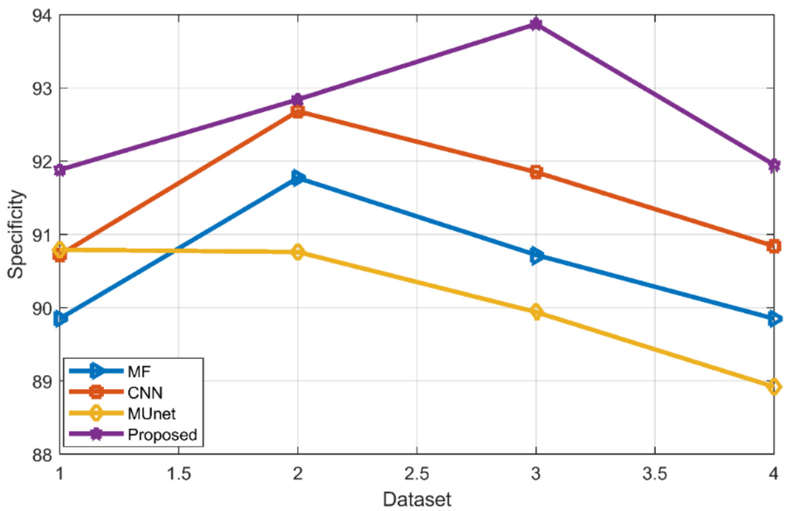

Fig 5 Comparative performance of specificity of Proposed, CNN, MF, and MU-net method using DRIVE dataset.

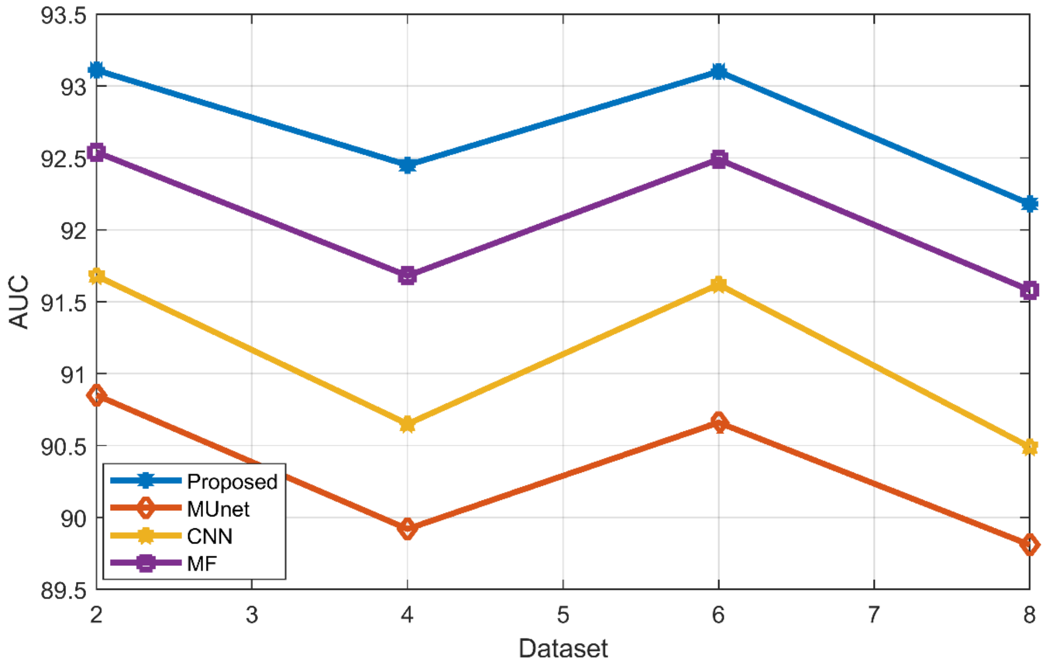

Fig 6 Comparative performance of AUC of Proposed, CNN, MF, and MU-net method using DRIVE dataset.

V. Results and discussion

this section explores results of proposed algorithm and existing algorithms of blood vessels segmentation on DRIVE datasets. The proposed algorithm evaluates standard parameters result shown in figure 3,4,5,6. The performance of the proposed retinal vessel segmentation model is compared against several established models, including CNN, MF, and MU-net. The comparison is based on key metrics across multiple test scenarios, highlighting the effectiveness and accuracy of each approach. The results indicate that the proposed model consistently outperforms the CNN, MF, and MU-net models across all test scenarios. The scores demonstrate the superior capability of the proposed model in accurately segmenting retinal vessels. With scores ranging from 92.88 to 93.91, the proposed model achieves the highest accuracy among all models. This indicates its robustness in handling various retinal image features and complexities. The scores are closely clustered, showcasing the model's reliability and consistent performance across different test cases. The CNN model shows strong performance with scores ranging from 91.69 to 92.87. While it is slightly less accurate than the proposed model, it still demonstrates considerable effectiveness in retinal vessel segmentation. The score variance is minimal, indicating a stable performance but not as high as the proposed model. The MF model's scores range from 90.88 to 91.78. While it is effective in capturing multiple features, it lags behind the proposed model and CNN in terms of accuracy. The moderate performance suggests that while MF is useful, it may require further optimization for better accuracy. MU-net model scores between 89.67 and 90.89, indicating the lowest performance among the compared models. Despite being a modified version of the U-net, it does not match the accuracy levels of the other models. The results suggest that MU-net may need enhancements or additional features to improve its segmentation accuracy. The proposed model demonstrates superior performance in retinal vessel segmentation compared to CNN, MF, and MU-net models. Its high accuracy and consistent results highlight its potential as a reliable tool for supporting the diagnosis and decision-making in ophthalmic diseases. The comparison underscores the importance of feature optimization and advanced deep learning techniques in improving segmentation outcomes.

VI. Conclusion & Future Work

The proposed algorithm is trained using a single dataset DRIVE which consists of 40 funds image. The proposed model able to segment blood vessels with accuracy and achieve mean F1 scores of 0.962, 0.996, and 0.905, respectively. Furthermore, figure 3 and 4 shows that the proposed algorithm outperforms the state-of-the-art for extracting CNN regions by 2.1%. The proposed algorithm ability to address heterogeneity within funds image obtained using various, as shown by the thorough analysis it conducted on the DRIVE dataset. The proposed algorithm also has the advantages of quick, adjustability, and reproducibility, which makes it a practical option for clinical practice. Indeed, a cost-efficient and accurate analysis of the funds image for the identification and segmentation of DR would be made possible by an automated and reproducible method, assisting ophthalmologists in clinical workflow and research. Additionally, rather than being based on a predetermined threshold or requiring an anatomical atlas, the MF-CNN predictions are based on local variations in intensity and radiological features within the blood vessel segmentation.

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