# MultiResUNet for Precise Segmentation of OpticDisc and Blood Vessels in Diabetic Retinopathy

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***Abstract*—Significance: Diabetic Retinopathy (DR), a widespread complication of diabetes, demands advanced diagnostic tools. This research is crucial in refining DR detection, offering potential advancements in patient care and early intervention.**
**Objective: The main aim is to enhance automated DR diagnosis by utilising the MultiResUNet paradigm. The main emphasis is on accurately segmenting blood vessels and optic discs to achieve higher precision and enhance diagnostic capabilities. The MultiResUNet is trained extensively using modern deep learning methods. The model is designed to accurately segment blood vessels and optic discs, enhancing its contribution to diabetic retinopathy diagnoses.**
**Results show significant accuracy in blood vessel segmentation (87%) and optic disc segmentation (98%). This sophisticated method represents a significant advancement in automated identification of diabetic retinopathy, especially beneficial in areas with a high diabetes prevalence.**
**Conclusion: The MultiResUNet model demonstrates high accuracy rates of 87% for blood vessels and 98% for optic discs, highlighting its effectiveness in performing precise segmentation tasks essential for automated DR diagnosis. This study highlights the importance of advanced deep learning methods and paves the way for further enhancements in automated detection of diabetic retinopathy.**

***Index Terms*—Keywords: Diabetic Retinopathy, MultiResUNet, blood vessel, optic disc, segmentation**

## I. Introduction

Diabetic retinopathy (DR) is a significant consequence of diabetes mellitus (DM) and continues to be a primary cause of visual impairment in working-age individuals. DR diagnosis is based on the clinical signs of vascular anomalies in the retina [1]. According to the International Diabetes Federation (IDF), there are now five hundred thirty-seven million adults living with high sugar level around the world. This is 74 million more than what was thought in 2019, which was a 16% rise. These new results, which came out before World Diabetes Day on November 14, show that the number of people with diabetes is rising at an alarming rate around the world. The most recent information comes from the IDF Diabetes Atlas, which will soon have its 10th version. The most recent IDF Diabetes Atlas indicates that diabetes now affects 10.5% of the global population, with nearly half (44.7%) of adults unaware of their condition. According to IDF projections, by 2045, 783 million adults will have diabetes, which is equivalent to one in eight adults. This represents a 46% increase, which is more than twice the projected population growth of 20% during the same timeframe [2].

The National Urban Survey found the following percentages in different metropolitan cities of India: 11.7% in Kolkata , 6.1% in Kashmir Valley, 11.6% in New Delhi and 9.3% in Mumbai. In comparison, Chennai (South India) had 13.5%, Hyderabad (South India) had 16.6%, and Bangalore (South India) had 12.4%. Additional research is needed in India to emphasise cultural and ethnic patterns and offer a more comprehensive insight into the variations in diabetes causes between Indian and other ethnic groups in the country [3].

For diabetics with type 1 and type 2, the most severe stage of the condition is called proliferative diabetic retinopathy (PDR). It happens when new blood vessels begin to form in the retina. We call this process neovascularization. These delicate new blood vessels can produce scar tissue and frequently leak into the vitreous. A retinal detachment caused by traction may result from this scar tissue is an extremely dangerous condition that can cause people to lose their peripheral and central vision. The length of the disease and the patient's age both increase the prevalence of all forms of DR in the diabetic population [4].

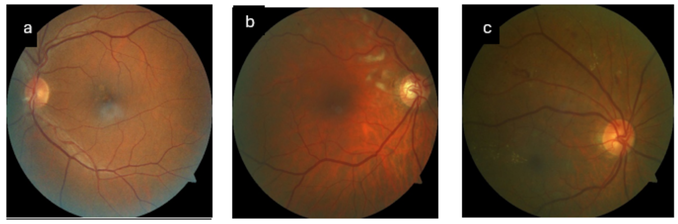


Fig. 1. Represents different stages of diabetic retinopathy.a) Mild NPDR b) Moderate N-PDR c) Severe N-PDR

. Hemorrhages in the retina are a crucial ocular diagnosticindicator of a systemic vascular disease. They vary in size from enormous sub-hyaloid haemorrhage to tiny dot and blot haemorrhages. It is also rarely observed idiopathically [5]. Most instances are minor, occur in children under the age of two, and are linked to severe coagulopathy, unintentional brain damage, and systemic infection [6]. 25% of newborns with normal births and 40% to 50% of newborns with instrumental deliveries experience birth-related retinal hemorrhages [7]. Thirty percent of children who were physically mistreated had retinal hemorrhages, with the majority of them being younger than six months old [8], [9].

DR attacks the retinal blood vessels in several ways, starting with the presence of microaneurysms in the initial stages as a sign of vascular weakness. Diagnosing DR is mostly dependent on the optic. It becomes the centre of pathological alterations as diabetes worsens. Comprehensive research is necessary to determine whether advanced proliferative diabetic retinopathy can exacerbate the effects of the optic disc.

Roychowdhury et al. [10] proposed a vessel segmentation method for fundus images. The approach involves morphological operations to remove large vessels and subsequent Convolutional Neural Network (CNN) classification of the sub-images. The method successfully separates vascular and non-vascular regions and provides accurate vessel segmentation, which lays the foundation for automated analysis of the retinal vasculature. Limitations, on the other hand, are potential challenges in handling vessel variations according to morphological features and the effect of data quality on the generalization ability of CNNs. Feng et al. [11] created automatic detection and diagnosis of retinopathy using a deep convolutional neural network (CNN). Trained with annotated fundus images of the blood vessels and optic disc, the model achieved accurate segmentation of the retinal structure, which contributes to the computer diagnosis of retinal diseases. However, the challenge is the possible limitations of the generalizability of the model, which arise from the diversity and representation of the educational dataset. Valverde et al. [12] discussed about the automated diabetic retinopathy detection, an important role in early disease iden- tification. As part of the detecting process, they use deep learn- ing more especially, a convolutional neural network (CNN) to separate the optic disc and blood vessels. Tsiknakis et al. [13] work focuses on automated detection of diabetic retinopathy, including segmentation of exudates, which are indicative of disease severity. The authors proposed a method utilizing image processing techniques such as thresh- olding, morphological operations, and feature extraction for exudate segmentation.

Valizadeh et al. focused on automated segmentation and feature extraction that is essential for early disease recognition [14]. Using fundus image datasets for CNN model training, they hope to improve the accuracy and efficiency of diagnosis. With its advanced technique for segmenting fundus images, this deep learning approach may enable quicker and more accurate identification of DR. Skouta et al. studied hemorrhage semantic segmentation in fundus pictures for the diagnosis of diabetic retinopathy [15]. Their work concentrated on automating the recognition and classification of retinal hemorrhages, a crucial early sign of diabetic retinopathy. Using the UNet architecture, they trained their model on datasets such as DIARETDB1 and IDRiD to create a reliable and effective technique for identifying possible areas of interest in fundus images. Meshal Alharbi et al. focused on improving the usage of a novel technique called Feature Fused U-Net (FFU-Net) to segment diabetic retinopathy (DR) lesions in fundus images [16]. Their paper discussed the difficulties in manually evaluating retinal health and suggests a better U-Net model for retinal vascular segmentation.

The MultiResUNet architecture has numerous benefits compared to conventional UNet architectures. Firstly, it utilises multi-resolution blocks, enabling the model to efficiently collect both local and global data. In addition, it incorporates residual connections within each block, which enhance the flow of gradients and simplify the training procedure. Moreover, the inclusion of skip links in the architecture allows the model to maintain spatial information and improve segmentation efficiency. Overall, the inclusion of these features enhances the performance of MultiResUNet in comparison to previous UNet variations, especially in intricate biomedical picture segmentation assignments.

The purpose of this study is to overcome the drawbacks of current segmentation techniques for retinal pictures, specifically in relation to diabetic retinopathy (DR). The study intends to enhance the accuracy and efficiency of retinal image segmentation by utilising advanced deep learning techniques, specifically the MultiResUNet architecture. This will improve diagnostic skills and enable early intervention for DR

The goal of the project is to use MultiResUNet to automatically separate blood vessels and the optic disc using DR fundus images. Quantitative metrics like Dice, the Jaccard coefficient,

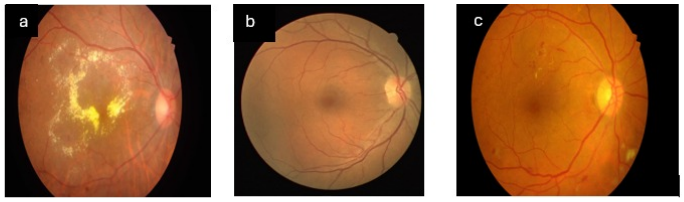


Fig. 2. Represents DR Fundus images of a Patient with Abnormal Retinal Eye that includes 2a) haemorrhage 2b) Blood vessel 2c) optic disc

and IOU were used to quantify the difference between the segmented image and the ground truth image.

## II. Methodology

### A. Data Collection

In this study, we used different fundus images to train and evaluate the MultiResUNet model for segmenting blood vessel and optic disc. Data sets selected for this purpose include the IDRiD (Indian Diabetic Retinopathy Imaging Dataset), DRIVE (Digital Retinal Images for Vessel Extraction) and STARE (Structured Retinal Analysis) and CHASE (Child Heart and Health Study of England). Each dataset contains retinal fundus images and corresponding manually annotated truth masks to enable supervised training of the MultiResUNet model.

IDRiD Dataset [17]: Retinal fundus photos from Indian patients with diabetic retinopathy are included in this dataset. These images were taken using different retinal imaging techniques and the exact boundaries of the optic disc, blood vessels and secretions were noted. We used part of the IDRID dataset for training and validation to ensure diversity of disease severity and image quality.

DRIVE dataset [18]: This dataset contains retinal fundus images of patients with diabetic retinopathy, focusing primarily on the vasculature for vessel segmentation tasks. Each image is manually labelled to mark retinal vessels, which serve as ground truth masks for training the MultiResUNet model. The photos were taken with a Canon CR5 non-mydriatic 3CCD camera with a 45-degree field of view (FOV). Using 8 bits per color plane, the image was captured at a resolution of 768 by 584 pixels. Each image has a field of view (FOV) that is approximately 540 pixels in diameter. A mask image that defines the field of vision is included with every photograph. Two sets of 20 photographs each, a training set and a test set, have been created from the original set of 40 images [18].There is just one manual segmentation of the vasculature accessible for the training images. Additionally, each retinal image has a mask image that shows the region of interest. An experienced ophthalmologist provided instruction and training to all human observers who manually segmented the vasculature. They were instructed to annotate every pixel for which they were at least 70% positive that it belonged to a vessel.

The STARE dataset [19] is made up of fundus pictures those were taken from patients with DR and marked in detail with the locations of the optic disc and vessels. Our goal in incorporating a part of the STARE dataset into our training data was to enhance the model's ability to accurately segment the optic disc and blood vessels.

### B. Pre-processing techniques

This study applied a standardized preprocessing pipeline to prepare retinal fundus images for training the MultiResUNet model. The original retinal fundus images from IDRiD, DRIVE and CHASE datasets have differences in resolution and aspect ratio. For consistency and computational efficiency during model training, we resized all images to a fixed resolution of 256 x 256 pixels. This resizing preserved the aspect ratio of the original images and reduced computational complexity and memory requirements.

After resizing, we used intensity normalization to normalize the pixels of the retinal fundus images. Normalization improves the convergence and stability of the training process by ensuring that pixel intensities are in the same range. Scaling the pixel values to the interval [0, 1] or dividing by the standard deviation of the pixel values after subtracting the means are two common methods of normalizing.

To increase the training dataset and improve the reliability of the system, we can apply data augmentation techniques. These techniques include random rotations, translations, translations, and scaling of retinal images. Adding data introduces variability to the training samples, during which the model learns invariant features and reduces overfitting.

Mask generation Next to the retinal fundus images, we took masks that were manually labelled by medical experts which was obtained from publicly available datasets, ensuring precise delineation of retinal structures. The masks were resized and normalized with the retinal images to maintain spatial correspondence.

### C. Segmentation and Model training

The MultiResUNet architecture is an advanced version of the UNet model designed for semantic segmentation tasks. It enhances the segmentation process by utilising multi-resolution features to effectively capture both local and global contextual information. MultiResUNet enhances UNet by incorporating a contracting path for contextual comprehension and an expanding path for accurate localization. The model incorporates skip links to combine characteristics from multiple resolutions, improving its capacity to capture fine details at different scales.

To train the MultiResUNet model, we standardise the resolution and normalise pixel values of retinal fundus pictures and

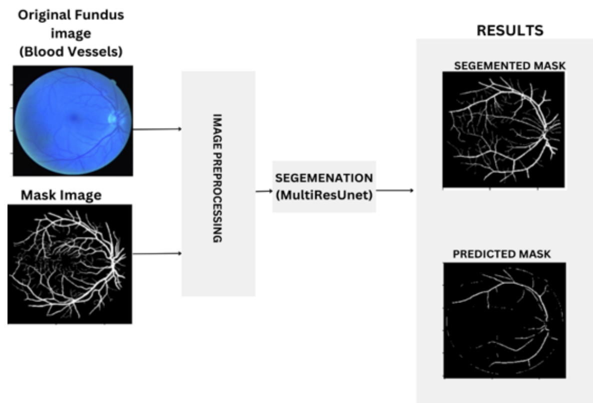


Fig. 3. Block Diagram of Proposed Work Flow

their related masks during preprocessing.
The recommended MultiRes block is used in place of the two convolutional layer series in the MultiResUNet model [20]. The number of filters utilized in the convolutional layers of each MultiRes block is determined by a parameter called W., which helps to keep a continuous correlation between the quantity of parameters. By applying the following techniques, we were able to ascertain W's value in both the suggested model and the original U-Net: This is the formula:

$$W = \alpha \times U \tag{1}$$

Here, U stands for the number of filters in each layer of the U-Net, and alpha is a scalar coefficient. Dividing W into U and alpha guarantees that the number of parameters is comparable to U-Net and makes controlling it easier. As feature mappings pass from the encoder to the decoder stages, convolution procedures are applied to them. As a result, we progressively decrease the quantity of convolutional blocks employed in the Res circuits. We employ 4, 3, 2, and 1 convolutional block sequentially along each of the four Res pathways. In the four Res routes, we employ filters with varying sizes (32, 64, 128 256) to correspond with the encoder-decoder's feature map count. Apart from the output layer, each convolutional layer in this network is batch-normalized and activated using the Rectified Linear Unit (Rectified) activation function.
The final layer is activated by Sigmoid function, similar to U-Net architecture The retinal fundus images and masks were pre-processed before being divided into training, validation, and test sets. For thorough model evaluation on new data, an 80-10-10 split was used. 80% of the distribution is allocated for training, with 10% each set aside for validation and testing. This partitioning technique facilitates effective model evaluation and adaptability to new, unobserved information beyond the training set by balancing learning, performance assessment, and generalisation.
We use a mix of loss functions, including cross-entropy loss and dice coefficient loss, together with optimisation methods like Adam to optimise the model parameters. The Adam optimizer adjusts learning rates for individual parameters to facilitate efficient model convergence during training. The learning rate, which is set at $1 \times 10^{-4}$, impacts the size of steps taken during optimisation, whereas weight decay aids in preventing overfitting by penalising excessive weights. Loss functions are essential for directing the model's learning process. The binary cross-entropy loss prioritises pixel-wise precision, while the dice coefficient loss highlights the resemblance between predicted and ground truth masks. Model performance is assessed on the validation set, and early stopping is applied to avoid overfitting [20].
Following the training of the MultiResUNet model, an additional test set is used for evaluation to measure segmentation accuracy and generalisation capability. Using a variety of retinal image datasets like IDRiD, DRIVE, STARE, and CHASE improves the training data and boosts the model's capacity to generalize across different retinal diseases and imaging scenarios. This thorough method enhances segmentation outcomes by accurately outlining optic disc, blood vessels, and other retinal components.

Finally, the pre-processed retinal fundus images and masks were passed to the MultiResUNet model for training. During training, the model learned to predict pixel-specific segmentation masks corresponding to the optic disc, blood vessels and secretions. The model parameters were optimized using gradient optimization algorithms such as Adam with the aim of minimizing the segment loss function. Following this preprocessing method, we ensured that the retinal fundus images were standardized and suitable for training of the MultiResUNet model [20].

### D. Quantitative Analysis

The following factors are considered when implementing quantitative analysis a few of them are listed below
Accuracy Definition: The total correctness of the model's predictions is gauged by accuracy. It determines the proportion of accurately anticipated cases to all instances.
SSIM Definition: The similarity between two photographs is measured using the SSIM metric. It provides a rating between

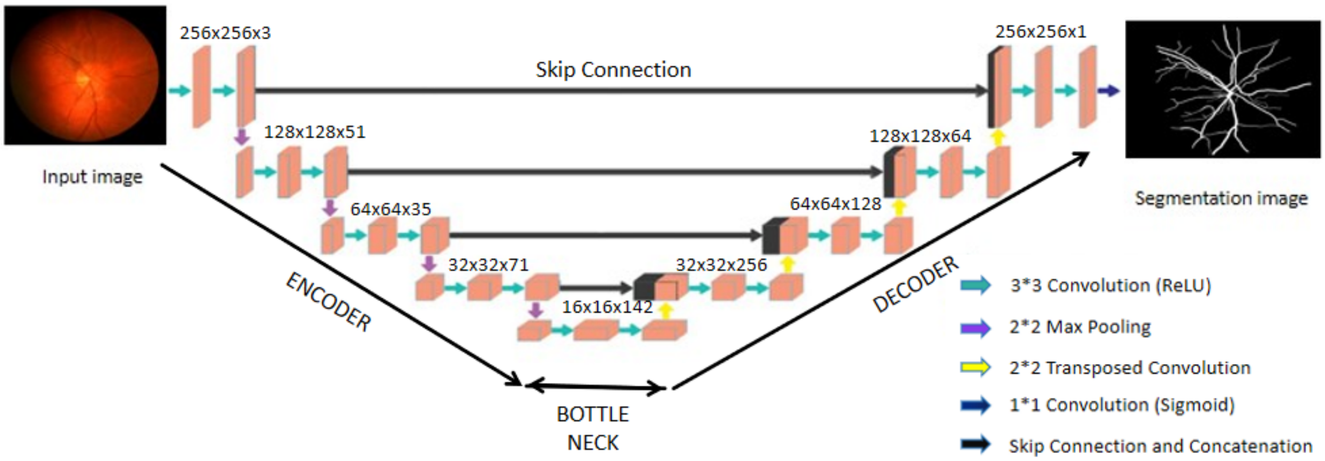


Fig. 4. Architecture of MultiResUnet Model

-1 and 1, where 1 denotes perfect likeness, after taking brightness, contrast, and structure into account. Specificity is a metric that quantifies a classification model's accuracy in identifying negative examples.

Jaccard Coefficient, often known as Intersection over Union (IoU): IoU is a metric that quantifies the proportion of the overlapping area between the predicted and actual areas compared to the total area included by both regions. It is commonly utilised in segmentation assignments.

In image segmentation tasks, the Mean Intersection over Union (IoU) statistic is commonly used to assess how accurate the predicted regions are compared to the ground truth. The measurement computes the ratio between the intersection area and the union area of the predicted and ground truth regions, producing a single scalar number that indicates the overall segmentation performance.

The Dice Coefficient, sometimes referred to as the Sørensen–Dice Index or F1 score, is a metric frequently utilised to assess the similarity between two sets. It assesses the consistency between the expected and actual binary masks in picture segmentation. The coefficient is determined by multiplying the intersection of the sets by two and then dividing it by the sum of their sizes, resulting in a number ranging from 0 to 1.

False Negatives / (True Positives + False Negatives) is the miss rate. The percentage of real positive cases that the model mis predicted as negative is known as the miss rate.

True Negatives / (True Negatives + False Positives) equals specificity. Specificity quantifies the percentage of real negative cases that the model properly classified as negative.

## III. Results

The MultiResUNet model was trained and evaluated on retinal fundus image datasets, including IDRiD, DRIVE, and STARE to assess its performance in segmenting optic discs, blood vessels. The model achieved promising results across all datasets, demonstrating its effectiveness in accurately delineating retinal structures.

Figure 3 retinal blood vessel was segmented using MultiResUNet for DR patients. Figure 3a) shows the retinal fundus image depicting the blood -vessels 3b) indicates the Mask image 3c) displays the anticipated output image created by Multi-ResUnet. Figure 4 depicts the retinal fundus image of DR which shows optic disc. Figure 4a indicates the retinal image depicting optic disk. Figure 4b represents the generated mask image of optic disk. Figure 4c indicates the segmented optic disk image.

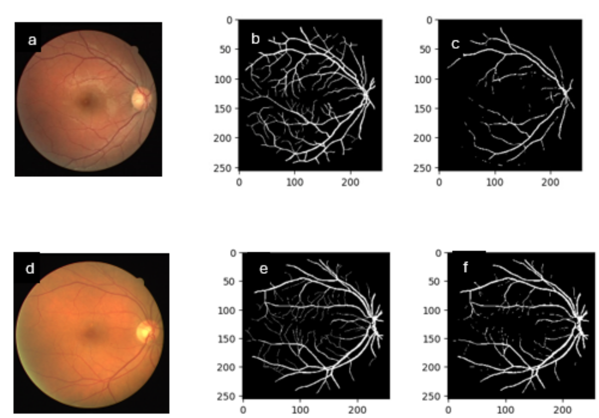


Fig. 5. Represents Fundus blood vessel image, mask and predicted mask for a patient without and with DR.a)original fundus image without DR b)ground truth image c) predicted output image d)original fundus image with DR e) ground truth image f)predicted output image

### A. Quantitative Evaluation

A quantitative assessment of the MultiResUNet model was conducted using industry-standard measures, such as the Dice coefficient, sensitivity, specificity and accuracy.

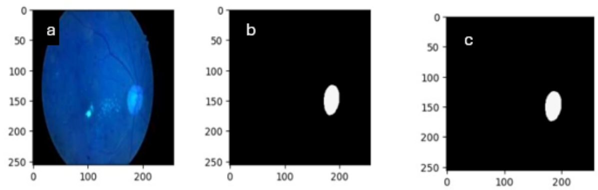


Fig. 6. Represents Optic disc image, mask and predicted mask of a patient with Diabetic Retinopathy. a) original image b) ground truth image c) predicted output image

TABLE I
QUANTITATIVE ANALYSIS OF BLOOD VESSELS AND OPTIC DISC SEGMENTATION IN DR FUNDUS IMAGES

| Metrics | Blood Vessels | Optic disc |
|---|---|---|
| Model Accuracy | 87.6% | 98.3% |
| Pixel-wise Accuracy | 87.6% | 98.3% |
| Fall out | 01.0% | 0.02% |
| Negative predictive Value | 97.7% | 99.9% |
| Specificity | 98.9% | 99.9% |
| Miss Rate | 02.2% | 0.02% |
| Mean IoU | 35.9% | 91.7% |
| Average Dice Coefficient | 64.8% | 44.1% |
| SSIM | 0.73 | 0.94 |
| Jaccard Coefficient | 97.85% | 99.57% |

## IV. DISCUSSION

The results show the effectiveness of the MultiResUNet model in accurately segmenting retinal structures from fundus images. The strong performance of the model across multiple datasets highlights its potential for clinical use in diagnosis and therapy of retinal diseases. In addition, the comparative analysis highlights the superiority of MultiResUNet over current segmentation methods in regard of both accuracy and efficiency.

MultiResUNet model showed outstanding performance in optic disc segmentation. The model's accuracy was 98%, demonstrating its capability to precisely detect optic discs. The Jaccard Coefficient achieved a remarkable 99.7%, demonstrating the model's accuracy in identifying the overlapping region between predicted and actual optic discs. The model demonstrated outstanding specificity of 99.9%, indicating its ability to accurately recognise true negatives inside all non-optic disc pixels. The IoU (Intersection over Union) mean value reached an amazing 91.7%, highlighting the model's precision in outlining optic discs. The SSIM (Structural Similarity Index) achieved a value of 0.94, demonstrating the model's skill in maintaining structural information in segmented optic discs. Table 2 shows how well the split optic disc in the suggested study compares to previous research. Table 3 shows how the segmentation of the retinal blood vessels in the proposed work compares to previous research. Table 3 indicates that the suggested work's precision is pixel accuracy.

Our model achieved an accuracy of 98.3% for optic disc segmentation, surpassing the accuracies reported in multiple studies. For example, Fan et al. [21] demonstrated an accuracy of 97.6%, whereas Abdullah et al. [24] reached 95.49%. Our model's specificity of 99.9% surpassed that of many references in the literature, demonstrating a high level of accurate identification of true negatives. The Jaccard coefficient of 99.57% shows outstanding similarity between the predicted and ground truth optic disc masks, exceeding values reported in previous studies. The model's performance demonstrates its robustness and effectiveness in accurately outlining the optic disc structure.

Our model attained an accuracy of 87.6% and a specificity of 98.9% in blood vessel segmentation. Although these metrics are praiseworthy, they are comparatively lower than certain references in literature. Qiaoliang Li et al. [26] achieved an accuracy of 95.27%, while Dashtbozorg et al. [27] reached 87.40%. Although slightly less accurate, our model demonstrates its ability to effectively capture the complex vascular patterns in retinal images, with potential for enhancement.

The neural network was trained for 700 epochs for optic disc and 500 epochs for blood vessels using Python 3.12. Computer specifications The processor is an Intel(R) Core(TM) i5-10300H CPU running at a speed of 2.50GHz, with 8GB of RAM. Some limitations in this model includes very less quantity of image taken for processing and the dataset were taken from online sites, rather than taking physically. In future the dataset can be taken physically with patients and the processing can be done.

In the future, we plan to explore the use of real-time data implementation, which is an important step in improving the practicality of our segmentation models in clinical settings. By embracing real-time processing, we expect to discover fresh opportunities for effortless integration into clinical workflows, thus propelling the area of retinal image analysis and diagnosis forward.

TABLE II
LITERATURE COMPARISON WITH RESPECT TO OPTIC DISC SEGMENTATION IN DR DIAGNOSIS

| Study | Accuracy (%) | Specificity (%) | Jaccard Coefficient(%) |
|---|---|---|---|
| Fan et al. [21] | 97.60 | - | 84.73 |
| Naqvi et al. [22] | 96.72 | 98.00 | 84.31 |
| Latif et al. [23] | 93.25 | 93.80 | - |
| Abdullah et al. [24] | 95.49 | 99.66 | 85.10 |
| Zahoor et al. [25] | 97.74 | 98.92 | 86.86 |
| Proposed work | 98.3 | 99.9 | 99.57 |

TABLE III
LITERATURE COMPARISON WITH RESPECT TO BLOOD VESSEL SEGMENTATION IN DR DIAGNOSIS

| Study | Accuracy (%) | Specificity (%) | Sensitivity |
|---|---|---|---|
| Qiaoliang Li et al. [26] | 95.27 | 98.27 | 75.69% |
| Dashtbozorg et al. [27] | 87.40 | 84.00 | 90% |
| Christodoulidis et al. [28] | 94.79 | 95.82 | 85.06% |
| Hoover et al. [29] | 93.48 | 93.84 | 67.47% |
| Proposed Work | 87.6 | 98.9 | 97.8% |

## V. Conclusion

Our study highlights the importance of using advanced deep learning methods, particularly the MultiResUNet architecture, for retinal image segmentation tasks. By utilising this innovative model, we successfully achieved a high level of accuracy in identifying the optic disc, with a precision rate of 98.3%, exceeding the values documented in existing literature. Our model showed high specificity and Jaccard coefficient, demonstrating its robustness in accurately capturing the boundaries of the optic disc. Our study on blood vessel segmentation achieved an accuracy of 87.6%, which is competitive, but identified areas for enhancement when compared to existing literature. However, the model's high specificity indicates its ability to accurately identify areas that are not vessels, highlighting its potential usefulness in clinical settings. Further refining and optimising the MultiResUNet architecture show potential for enhancing segmentation accuracy and generalisation abilities. Our study provides valuable insights into using deep learning methods for analysing retinal images, showing promise for enhancing the diagnosis of DR and patient care.

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