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Retinal Image Segmentation for Diabetic Retinopathy Detection using U-Net Architecture

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Abstract: Diabetic retinopathy is one of the most serious eye diseases and can lead to permanent blindness if not diagnosed early. The main cause of this is diabetes. Not every diabetic will develop diabetic retinopathy, but the risk of developing diabetes is undeniable. This requires the early diagnosis of Diabetic retinopathy. Segmentation is one of the approaches which is useful for detecting the blood vessels in the retinal image. This paper proposed the three models based on a deep learning approach for recognizing blood vessels from retinal images using region-based segmentation techniques. The proposed model consists of four steps preprocessing, Augmentation, Model training, and Performance measure. The augmented retinal images are fed to the three models for training and finally, get the segmented image. The proposed three models are applied on publically available data set of DRIVE, STARE, and HRF. It is observed that more thin blood vessels are segmented on the retinal image in the HRF dataset using model-3. The performance of proposed three models is compare with other state-of-art-methods of blood vessels segmentation of DRIVE, STARE, and HRF datasets.

Index Terms: Diabetic Retinopathy, Retinal Images, Blood Vessel, Region-based Segmentation, Deep Learning, DRIVE, STARE, and HRF

1. Introduction

The number of patients with type 1 and type 2 diabetes has been increasing worldwide for the past few years. Patients with chronic diabetes have an increased risk of developing diabetic retinopathy, which can lead to permanent loss of vision. Initially, there are no symptoms of diabetic retinopathy. Also, there are no visual problems. But in the end, man can become completely blind. People with type 1, and type 2 diabetes are more likely to have diabetic retinopathy. An uncontrolled rise in blood sugar in a diabetic patient is a major cause of diabetic retinopathy. Excess blood fats, low hemoglobin levels, chronic diabetes, tobacco, cigarette addiction, alcoholism, stress, etc. all contribute to diabetic retinopathy. Patients with eye problems have been shown to have diabetes and such patients need to be more vigilant. If diagnosed early, diabetic retinopathy disease can be controlled.

Over the last several years, numerous research groups have looked into the topic of blood vessel segmentation in fundus retinal images. In recent years, deep learning-based algorithms have gained popularity for a variety of computer vision-based applications, such as object detection and image segmentation on retinal images. In clinical applications,

although, networks must be modified to account for problems specific to each diagnostic tool, such as structural features and spatial resolution. Several types of research looked into the differences in image quality and disease. Various organisations have thoroughly investigated the issue of retinal blood vessel segmentation in fundus imaging during the past number of years. The majority of the currently used methods make use of particular instance in image processing technologies and due to variations in sampling strategies, lighting, colour, disease, and image quality, and are frequently challenging to generalize.

This research is focused on segmenting the blood vessels for the early detection of diabetic retinopathy. This paper proposed the three deep learning models on the DRIVE, STARE, and HRF datasets. The performance evaluation of three models has been measured using parameters such as sensitivity, specificity, and accuracy on the publically available data set of DRIVE, STARE, and HRF. The main objectives of this research are as follows:

- Proposed the layered architecture based on U-net for retinal image segmentation in early detection of DR.
- The proposed model uses edge-based segmentation techniques for detecting the more thin blood vessels for segmentation.
- The proposed models obtained state-of-art results for edge-based segmentation and compared with existing state-of-art methods.

2. Related Work

A number of various machine learning techniques and methods were proposed by the various researcher for the detection of retinal blood vessel segmentation. Several articles addressing ML and DL algorithms for colorful clinical retinal blood vessel images segmentation have been reported [1, 2], while spatial and spectral segmentation has seen a great amount of progress [3, 4]. In [5], suggested the recent advancement in artificial intelligence for automatic detection of diabetic retinopathy over the retinal fundus images.

In [6], proposed the model for retinal vessel segmentation on fundus camera images based on the multiwavelet kernel and multiscale decomposition approach on two DRVIE and STARE datasets. The proposed model classifies the retinal images on two types of vessels or non-vessels using a pixel classifier. The final result shows a better accuracy level of 94% as compared to existing methods. In [7], proposed the model of retinal image vessel detection based on the Cauchy on the DRIVE dataset. The proposed approach utilized the kernel function and Gaussian function for feature extraction. The other approach proposed [8] for retinal image segmentation is based on watershed transformation, contrast map, and directional map approaches.

The model utilized the DRIVE retinal image dataset. In [9], the author proposed the deep convolutional model for retinal image segmentation without preprocessing the image. The proposed model utilized the DRIVE and HRF datasets. although final results were measured in terms of accuracy which was 93%. Another segmentation technique [10] was proposed for the detection of a blood vessel on the DRIVE, STARE, and CHASE datasets. In contrast, normalization, geometric transformation, and gamma correction functions were used for image augmentation. Although, the final result shows a better accuracy level in terms of ROC which was up to 97%. Another approach Bag of Visual Words [23] was used for the identification of retinal images based on the probabilistic Latent Semantic Analysis technique. The proposed approach used low-level features. The SVM classifier was used for retinal image classification. The automatic segmentation of blood vessels based on a deep convolutional model was proposed in [24]. The model utilized the up-sampling and down-sampling approaches in layers. The performance of the model was measured on DRIVE, STARE, and CHASE_DB1 datasets in terms of accuracy, sensitivity, and specificity. Another supervised learning classifier model was proposed in [25] for retinal image classification based on a grading approach and pre-training the neural network for unlabeled multidimensional retinal images. The Bayesian baseline [26] approach was used for lesion segmentation to measure the uncertainty of the false classification. In [27] proposed the automatic multitask segmentation approach on publically available IDRiD, E-Ophtha, and Messidor performed the pixel-wise segmentation of retinal microaneurysms, hard exudates, and optic disc. In [28], proposed the Convolutional neural network model for detecting the Exudate on retinal images using the Circular Hough Transformation method. In [29], proposed deep learning model for retinal blood vessel segmentation. For the preprocessing s Contrast Limited Adaptive Histogram Equalization approach was used. For feature extraction Tandem Pulse Coupled Neural Network was used and finally for the classification of retinal blood vessels deep learning-based SVM model was proposed. In [30] proposed deep learning based on the model for diabetic retinopathy image classification based on transfer learning [31] and a hyperparameter was utilized.

To enhance the formulation, the certain neural model features in the research preserve hierarchical-based characteristics in each stage of the model. In [32] suggested a fully connected Convolution model that feeds characteristics through one layer to the next layer based on a feed-forward manner. In [33] suggested a CcNet model that integrates part of the layer features in-between places over an interconnected CNN model. U-Net [34] as well as its related designs introduced in [35] and [36] use an identical strategy to increase a model training capability by combining previous layers' characteristics with the next layers.

The edge-based segmentation technique is modelled after traditional methods like the Morphological operators, Robert's operator, and Gabor filter and Trilateral Filter [37, 38]. The technique uses a Gabor and Trilateral filter as an

initial stage, however at first, pixels are examined to see if they meet a specific requirement. Gabor filter can generate any required edge detection, in contrast to other edge-based approaches that only provide a total edge map [39]

Table 1 shows the summary of previous related work on blood vessel segmentation in various available datasets of the retinal image.

Table 1. Summary of related work on blood vessel segmentation

Ref.	Database Used	Methodology	Classifiers	Accuracy in %
Wang et al., [6]	Drive/Stare	Multiwavelet Kernel	Pixel	Acc. 94.6 Acc. 95
Zolfagharnasab et. al. [7]	Drive	Cauchy matched filter	---	Acc. 91
Frucci et al., [8]	Drive	Watershed Transform	Pixel	Acc. 96
Vengalil et al., [9]	HRF	ReLu and COCO	CNN	Acc 93
Liskowski et. al. [10]	Drive/Stare/ Chase	GCN, ZCA	CNN	Acc. 95
Jiang et al. [11]	Drive/Stare	Morphological	---	Acc. 95
Oliveira et al. [12]	Drive/Stare/Chasedb1	Stationary Wavelet Transform	CNN	Acc. 95 Acc. 96 Acc. 93 Acc. 96
Sathananthavathi et. al. [13]	Stare	Gaussian filter	RF and BAT	Acc. 95
Hua et al. [14]	DRIVE	ReLu	CNN	Acc. 95
Tian et al. [15]	DRIVE/Chasedb1	Gaussian low pass filter/ Gaussian high pass filter	CNN	Acc. 95 Acc. 96

3. Proposed Methodology

This research work proposed a model based on the U-Net architecture in Deep Learning for the detection of blood vessels in retinal images using segmentation. Figure 1 shows the complete architecture of the proposed system which consists of several steps such as Preprocessing, Augmentation, U-net model, Segmentation, and predicted result.

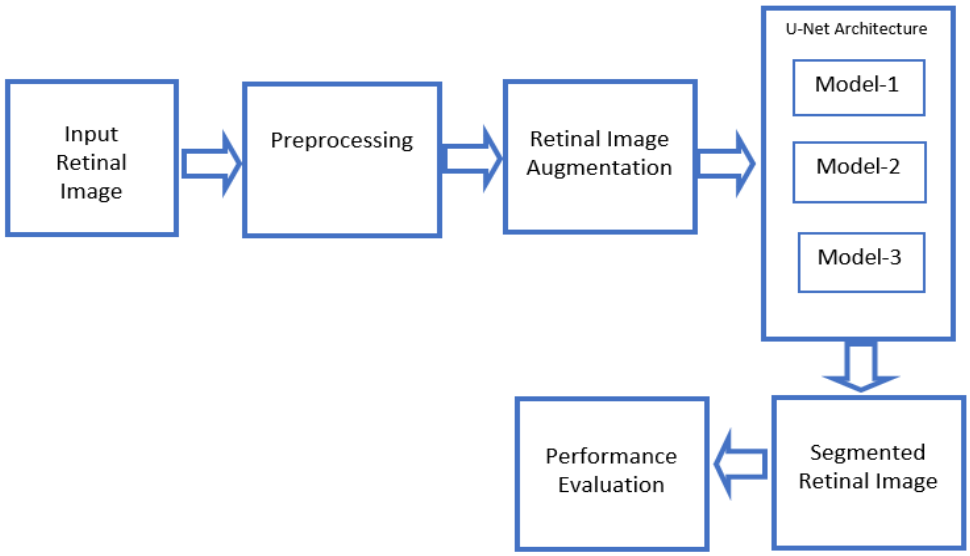

Fig. 1. Complete Architecture of the Proposed System

3.1 Dataset used

As far as we know, there are 9 openly accessible retinal datasets. Only three of them such as DRIVE, STARE, and HRF has been utilized for this research which is publically available on Kaggle. Table 2 shows the total number of retinal images and a total number of images after augmentation though, offer real images with expert annotations. Considering are all of reasonable quality, the DRIVE, STARE, and CHASE DB1 datasets are frequently recommended in the previous literatures. Due to its recentness and significantly higher imaging quality than the DRIVE and STARE datasets, the HRF dataset is often neglected in retinal blood vessel segmentation research.

Table 2. Retinal Image Datasets

Database	Original Retinal Images	Image Size	No. of images after augmentation
DRIVE	20	565 * 584	120
STARE	20	700 * 600	120
HRF	15	3304 * 2336	90

3.2 Pre-processing using Image Augmentation

Augmentation is the process of modifying the existing captured fundus images in order to generate more fundus images for training the proposed model by transforming, rotating, flipping, and cropping the images. It is important for improving the performance of the proposed U-net model. The proposed model uses hyperparameters to obtain important or optimal features. The setting of hyperparameter is, Initial learning rate is 1 * e-4, total 32 batch size. epochs size is 50. The Model uses dice loss function and Adam optimizer for optimal feature extraction. Figure 2 shows the different augmentation techniques. It uses the horizontal flip, vertical flip, grid distortion, elastic transformation, and optical distortion on the fundus image. The original retinal image is augmented based on various operations like Horizontal, and vertical flip with the 0.6 probability, elastic transform is 0.2, grid distortion is 0.2, and optical distortion is 0.2. This feature is used in the model to get the best results.

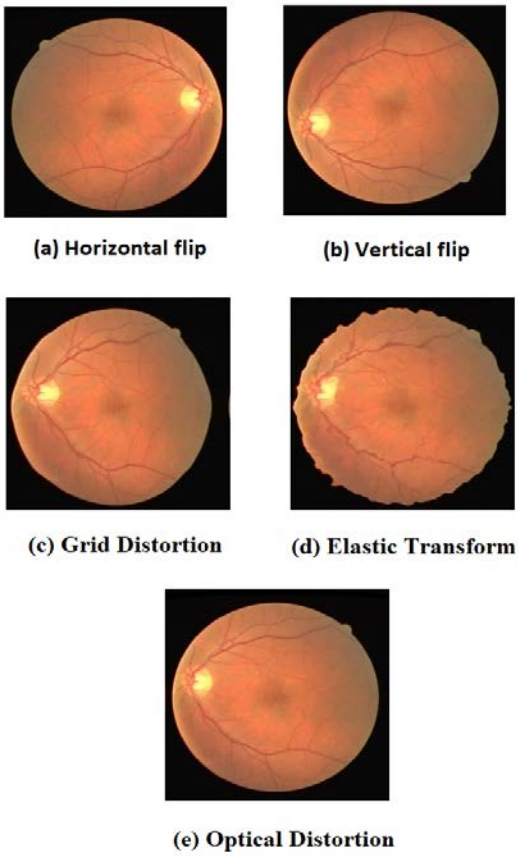

Fig. 2. Retinal Augmented Images

3.3 Proposed Model Training and Testing

This paper proposed three U-Net models. The first model is the basic model of U-Net architecture with three levels and the second and third models are based on the basic architecture with one layer added in each. This is the novelty of research work. Each model consists of three block encoders, the Convoluted and the Decoder. Each model has a layer in the encoder/decoder block and the number of channels in it is constantly changing. Used a pooling layer to reduce the location value and data of the encoding block and to extract the corresponding feature. Accurate positioning by pixel features identified by local and decoding layers. These local features were combined with the new feature map while using the previous down-sampling approach to retrieve information on some important features using the up-sampling approach. Figure 3, figure 4, and figure 5 show the three proposed U-net models. The dashed line in models represents the one-to-one interaction between layers of encoder/decoder block which helps the model preserve the low-level

characteristics. In the U-Net model, set the starting value of the encoder block to 64. After the pooling padding operation, the value of each layer is set to double. Retinal images of size 512 * 512 are given in the convoluted block and reduced error rates using batch normalization and max-pooling operations and retaining texture information of retinal images. The up-sampling method is used for reducing the retinal image size in the decoder section and matching it with the original retinal image size in the encoder block. These models used 70% of the dataset for model training and 30% data for model testing to predict the segmented retinal image

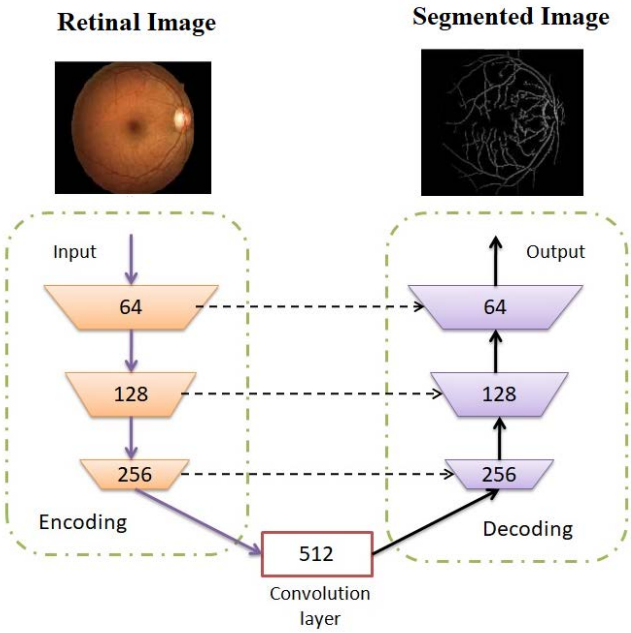

Fig. 3. Three-layer U-net Architecture (Model-1)

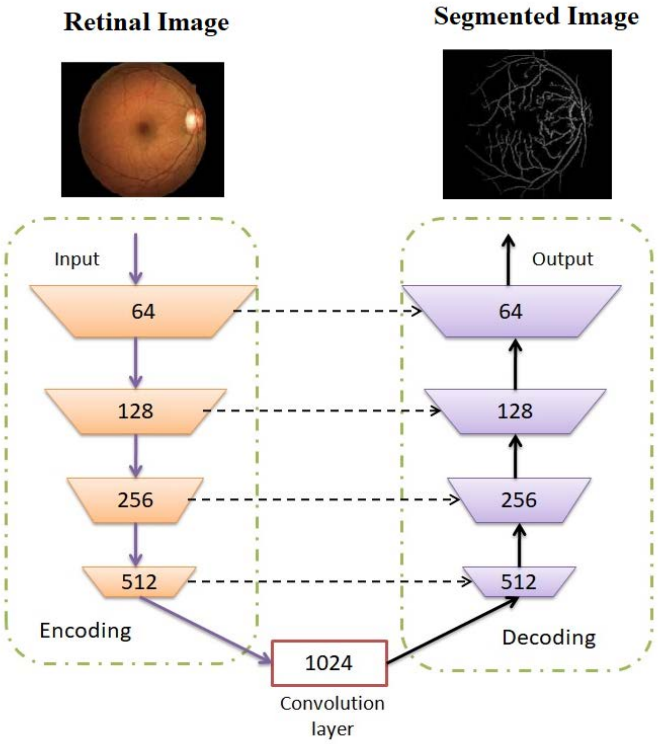

Fig. 4. Four-layer U-net Architecture (Model-2)

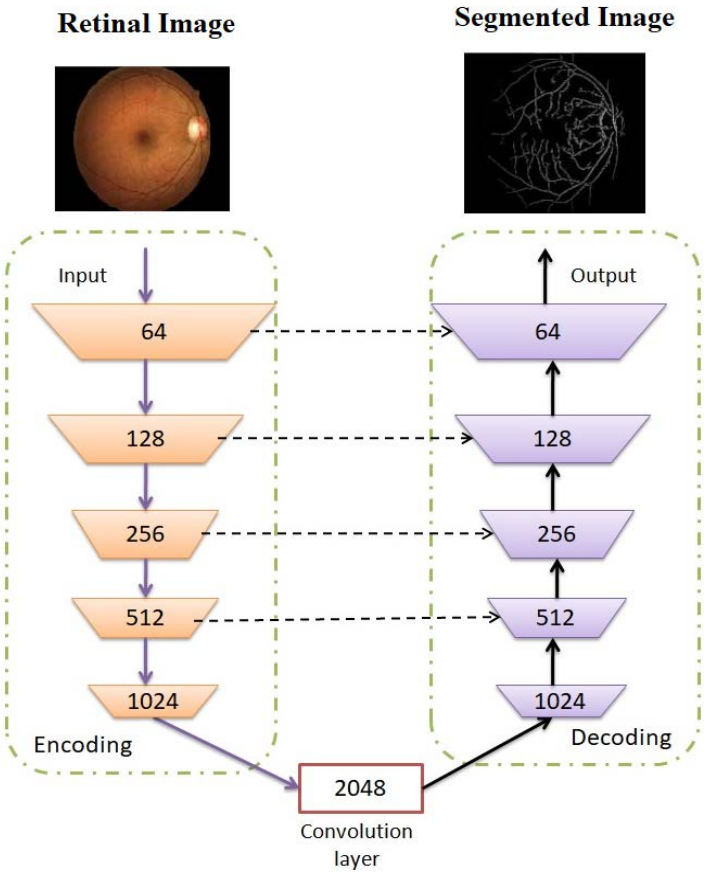

Fig. 5. Five-layer U-net Architecture (Model-3)

3.4 Proposed Algorithm

Figure 6 shows the layered architecture of the proposed model, in which e1, e2, etc. are encoder layers and d1, d2, etc. are decoder layers. Every encoder layer contains a convolution 2d block which identifies a number of filters used by the convolution layer. U-Net is the simpler and faster than fully convolutional networks since it only uses the valid portions of every convolution layers. Cross-connections between the expanding and contracted paths also aid in creating output for segmentation that is highly reliable. There are four blocks of encoding units make up U-contracting Network's channel. Two convolution layers are applied to each encoder units before the max pooling layer. Every pooled procedure increases the number of features. Two convolutional layers and just one up convolutional layer make up the bottleneck, which is the portion of the channel between the growing and shrinking routes. The growing route of U-Net is made up of four decoding units, every of them has two convolutional layers, a deconvolutional layers, and a clipped feature space from the convolutional layers. An Encoding layer on the left-hand side and a symmetrical expanding channel decoding on the right-hand side provide the improved U-Net design as shown in Fig. 6 so that its U-shape. To improve localized precision, a merging layers is added after the decoding. The outputs of the previous block to be upsampled and activating features are sent from an intermediary layer of the encoding layer and decoding layers in U-Net. By using the output of the convolutions that have been carried on and the cross-connection of the source images, the ultimate pixel-wise segmentation output image is produced.

After convolution batch normalization is used to standardize the inputs to layer for each mini-batch. The activation function is used in every layer, at the input layer and dense layers “Relu” is used as an activation function. After activation max-pooling layer is applied to every encoder layer. The same functions are applied to decoder layers for identifying the final output. Three models are tested on test data for predicting segmented images. The best model is identified based on performance evaluation using different measures which are mentioned in a further section. Figure 6 presents the flow of vessel segmentation using different events and components. These events and components are represented in the algorithm using different functions used for implementation. The proposed models to help achieve research objectives. The absence of fully-connected layer at the ends for retinal vessel identification is to achieve first objectives. Since completely connected layers typically contain an intensive multiplier, the trait enhances train and fast respond of predictions. The third benefit, as previously indicated, is because proposed models keep picking up new features while downstream and up-sampling. The proposed models capacity for learning is enhanced in that manner.

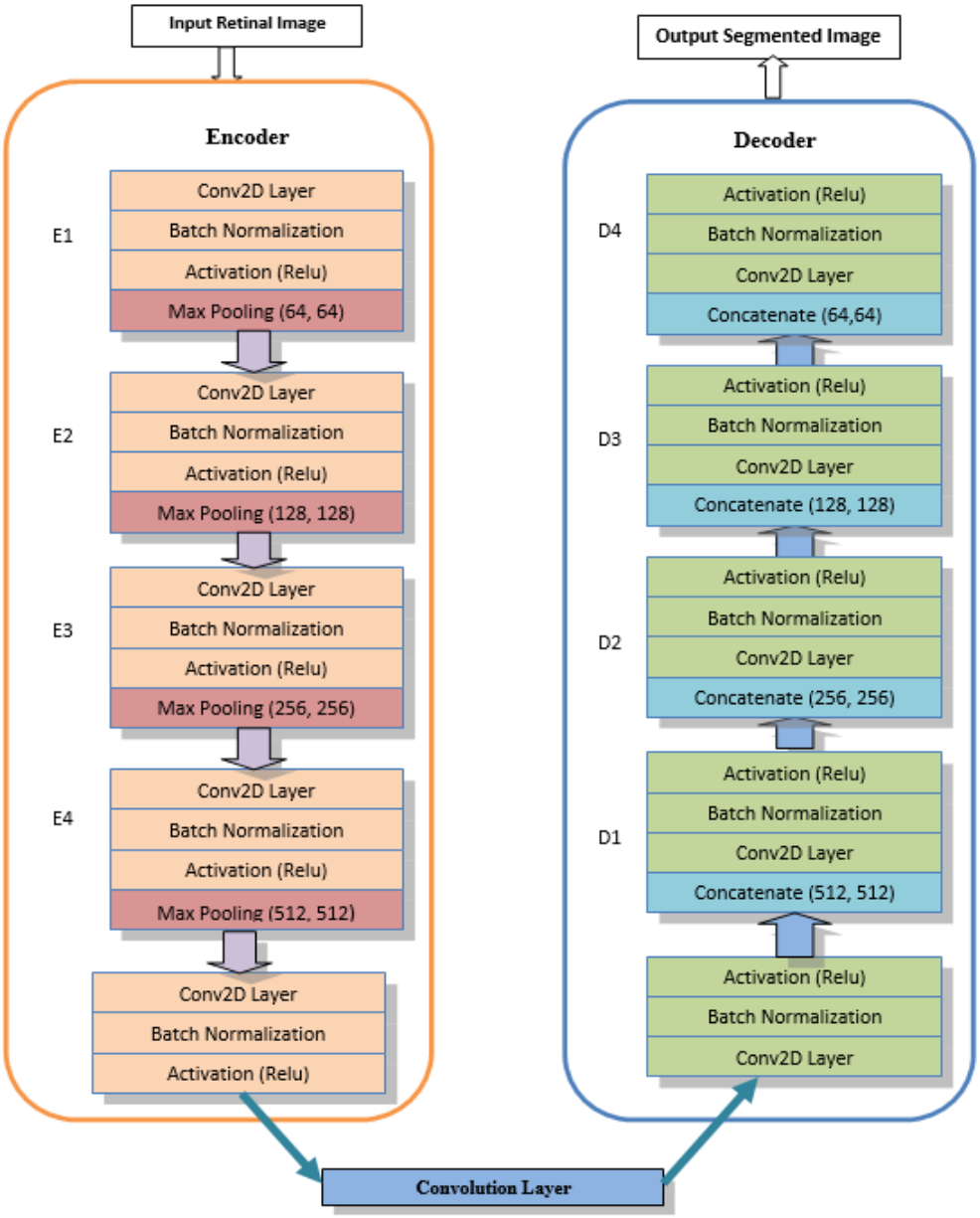

Fig. 6. Layer architecture of the proposed model

3.5 Edge-based Segmentation

The proposed edge-based segmentation technique is used in the proposed model in which each pixel is reached in turns, the starting point is the top left corner of retinal images, and scans each row up to the bottom right corner of the retinal image. For every non-edge pixel (p, q), The necessary criteria must be met. If has recently visited the neighbors.$(p - 1, q)$ and $(p, q - 1)$ for 3-layer case, also $(p - 1, q - 1)$ for 4-layers and $(p - 1, j + 1)$ for 5-layer case. For all edges, set the new class and (p, q) is allocated to it. While, on the other hand, all of its non-edge neighbouring pixels belong to the same group, then (p, q) is set to this group. Last but not least, neighbouring pixels may fall into more than two groups in which (p, q) is assigned to one of the groups, and a notation is made that such groups are linked and treated as a singular group.

The initial group value is set to $N = 0$

Examine each pixel (p, q), scan each row $p = 1, 2, 3, \ldots . n$, and every value of p takes $q = 1,2,3 \ldots n$.

4-probabilities are set to pixel (p, q)

a. If Pixel (p, q) value is found on edge, nothing to do.

b. If previous visited neighbouring pixel $(p - 1, q)$ and $(p, q - 1)$, is on edge then a new group has been made for (p, q)

$$N -> N + 1, r_N = N, c_{pq} = N \quad (1)$$

While $r_1, \ldots, r_n$records are required to maintain the count among which groups are similar, and c_{pq} store the group label for each pixel (p, q)

If one of the two adjacent pixels is on the edge of the pixel, the other (p, q) will be given the same label:

$$c_{pq} = \begin{cases} c_{p-1,q} & if\ (p, q-1)\ is\ on\ edge \\ c_{p,q-1} & Otherwise \end{cases} \quad (2)$$

The last possibility is that there are no adjacent edge pixels, in that case (p, q) is labeled as one of them

$$c_{pq} = c_{p-1,q} \quad (3)$$

Moreover, if the neighbours pixel already has labeled are not indicated as same, so that, $r_{c_{p-1,q}} \neq r_{c_{p,q-1}}$Therefore it must be completed (since linked at the pixel level (p, q)). This similarity is noted by making the following changes to the elements in $r_1, \ldots, r_n$

$$Set\ \ L_1 = \min\left(r_{c_{p-1,q}}, r_{c_{p,q-1}}\right)\ \text{and}\ L_2 = \max\left(r_{c_{p-1,q}}, r_{c_{p,q-1}}\right) \quad (4)$$

For each value of n from1 $to\ N$, $\quad if\ r_n = L_2\ then\ r_n \rightarrow L_1$

Lastly, the matrix of names is changed after all the pixels have been evaluated, taking into consideration which groups have been indicated for merging:

$$c_{pq} \rightarrow r_{c_{pq}}\ \text{for all}\ p, q = 1,2,3 \ldots \ldots . . n \quad (5)$$

The proposed models have been simulated with on the Keras API and TensorFlow framework based on a deep learning approach. Three models are tested using the various hyperparameter which is already discussed in section 2. For a wide range of issues, the Adam optimizer is the best option. The categorical cross-entropy loss function L is reduced for 10 epochs in the proposed model. The loss function for categorical cross-entropy is defined in Equation 6. The learning rate is 1e-4. Experiments were performed for epoch 10 with batch size 4. In equation 1 y is the original image and yˆ is the predicted image and Q is the number of training samples and R is the number of categories.

$$L(y, \hat{y}) = -\sum_{r=0}^{R} \sum_{q=0}^{Q} (y_{q,r}, \log\left(y_{q,r}\right)) \quad (6)$$

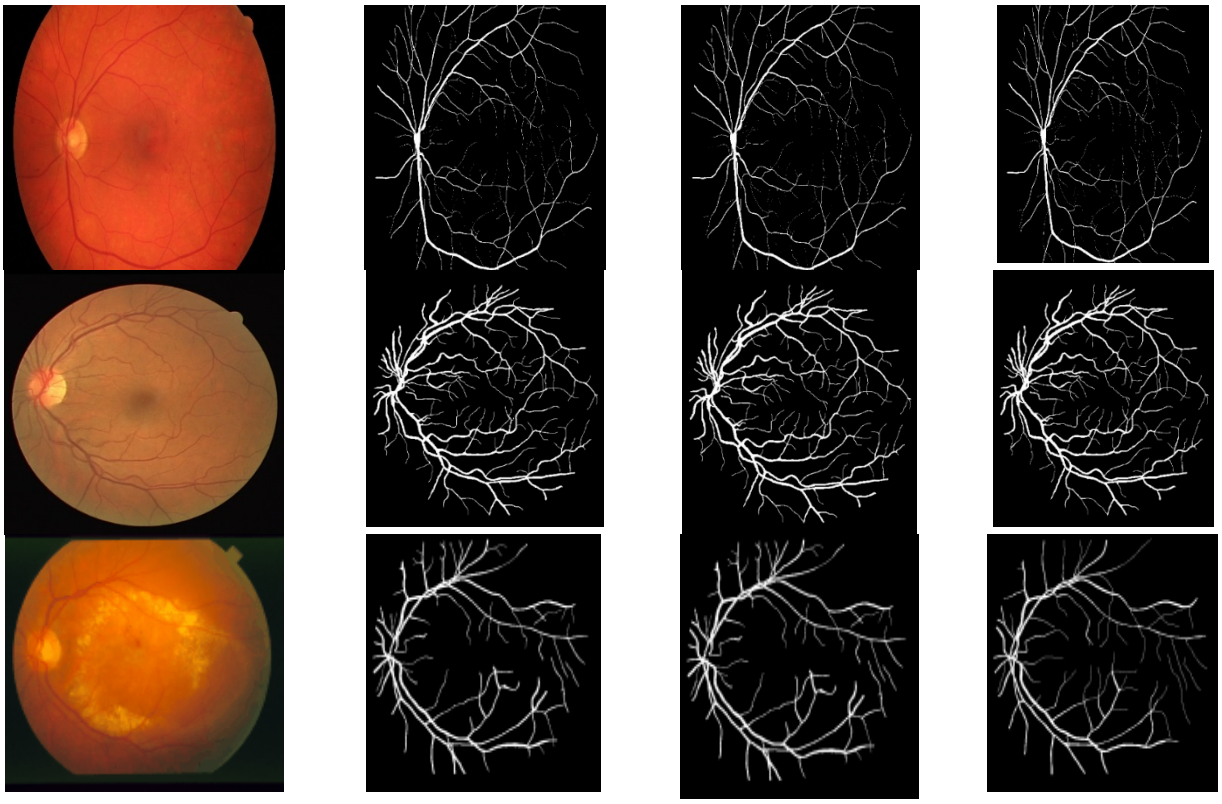

Fig. 7. Blood Vessel segmentation of proposed Model. First Represent the test image of the HRF dataset. The second row represents the test image of the DRIVE dataset, and the Third Row represents the test image of the STARE dataset. The first column represents the original retinal images.

3.6 Parameter Evaluation

With regards to the ground truth of the three data sets HRF, DRIVE, and STARE, evaluate the percentage of pixels that were correctly identified as retinal vessel in order to assess the method's effectiveness quantitatively. Accuracy, Sensitivity, and Specificity are the three evaluating measures that are used to compare each training and effectiveness of all models.

$$Acc. = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{7}$$

$$Sens = \frac{TP}{TP+FN} \tag{8}$$

$$Spec = \frac{TN}{TN+FP} \tag{9}$$

4. Results & Discussion

The effectiveness of every training sample for the U-Net model suggested in this research is presented in this result section. The local and cross datasets testing that are presented in table 3 are performed using different testing datasets. In this section, also examine into the impact of preprocessing. Since the size of all retinal dataset image varies, it should be found that data augmentation techniques like horizontal flip, vertical flip, grid distortion, elastic transformation, and optical distortion may result in blood vessel that go beyond the edges of images. In order to make the all the models input size suitable with proposed approach of data augmentation, use 448×448 size of images. It Split testing retinal images into the fewest amount of patch necessary to put every patched into the inputs because the testing data images are larger than the model input size. When generating the results, consider a weighted sum of forecasts for the overlapped areas in the patch. The proposed three models are based on U-net architecture for blood vessel segmentation on the retinal image's dataset. The performance of the three models is shown in figure 8, figure 9, and figure 10 on the three different datasets respectively. Table 3 shows the performance evaluation and comparative analysis of all three proposed models on three datasets. It is observed that more thin blood vessels are segmented on the retinal image in the HRF dataset using model-3. And also, it is observed that model-2 gives a good result for DRIVE and STARE datasets. It has been found that encoder and decoder layers give more significant results when extended in the basic U-net model.

Table 3. Performance Evaluation and Analysis Of Three Models

Dataset	Model-1			Model-2			Model-3		
	Spec.	Sens.	Acc.	Spec.	Sens.	Acc.	Spec.	Sens.	Acc.
HRF	92.90	67.44	95.70	93.69	67.70	93.43	91.49	81.82	93.10
DRIVE	93.05	65.92	93.52	94.81	93.30	93.86	93.02	90.07	93.47
STARE	94.47	70.40	92.72	93.60	89.04	93.07	93.78	73.94	92.60

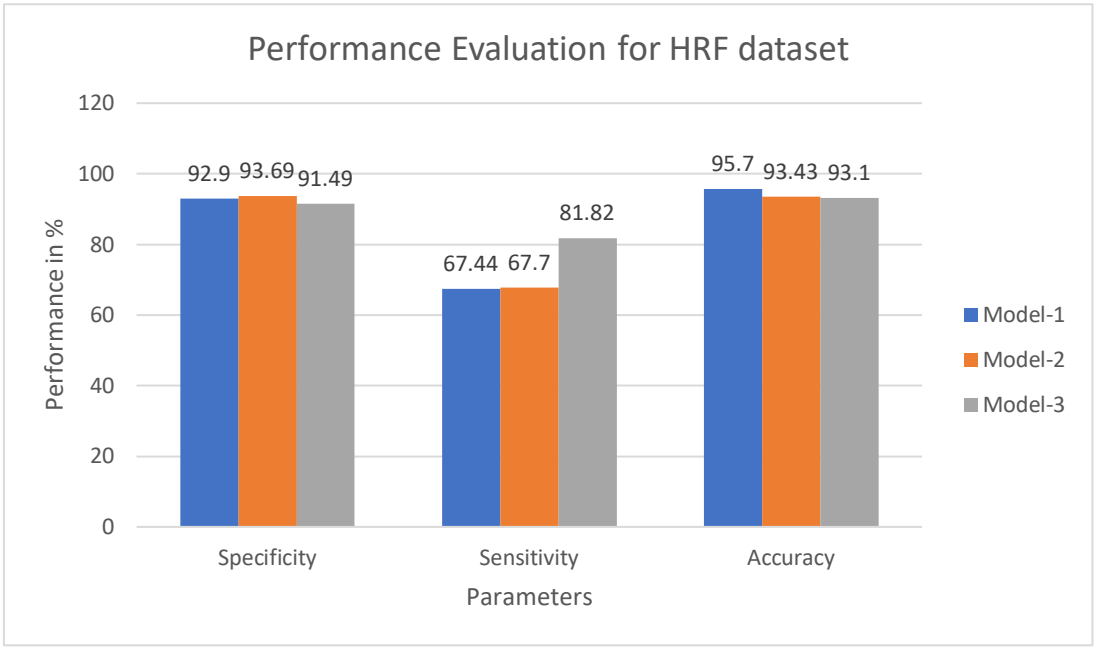

Fig. 8. Performance Evaluation of Models on HRF dataset

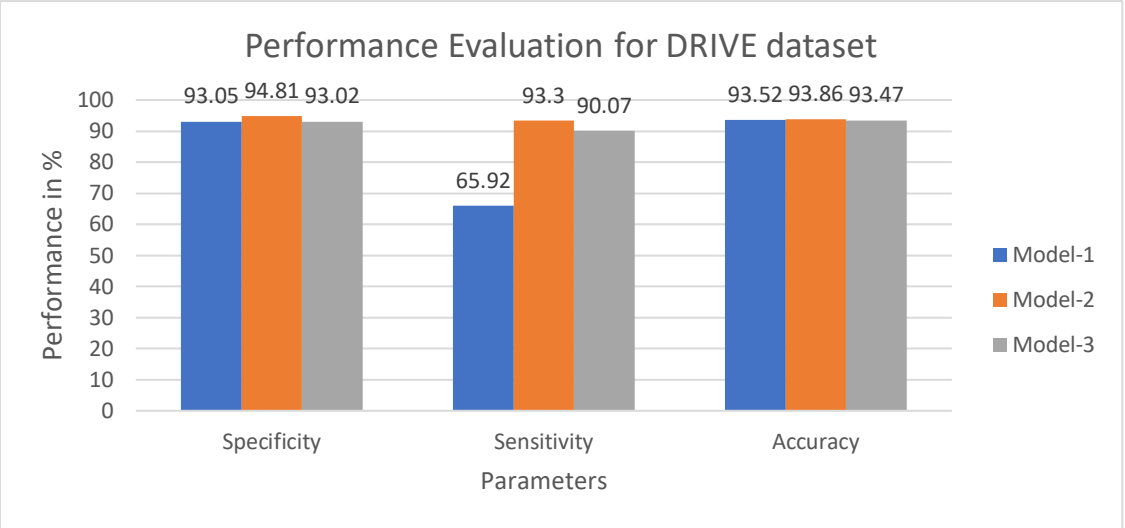

Fig. 9. Performance evaluation of Models on DRIVE dataset

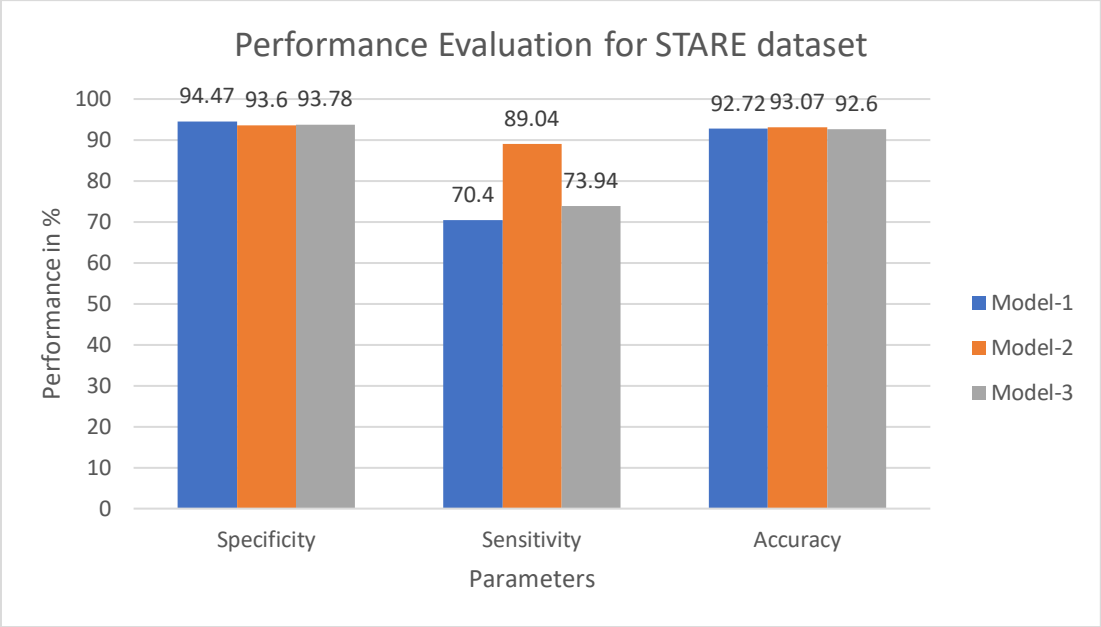

Fig. 10. Performance evaluation of Models on the STARE dataset

4.1 Discussion

Several previous researches has been done in the field of retinal image segmentation in DR and compares the proposed models with the existing state-of-art methods of blood vessels segmentation of DRIVE, STARE, and HRF datasets. We concentrate on largely supervised approaches for a valid comparative analysis because proposed models rely on deep classification. To evaluate image segmentation capability of proposed models and also take into account an image segmentation effectiveness. Figure 11 shows that model-2and model-3 gives better result as compared to Azzopardi et. al. [16], Maninis et. al. [17], Vlachos et. al. [18] for the DRIVE dataset. Figure 12 shows that model-2 gives better results as compared to Azzopardi et. al. [16], A. M. Mendonca et. al. [19], Mo J. et. al. [20] for the STARE dataset. Finally figure 13 shows that model-3 gives better results as compared to Li et. al. [21], K. B. Park et. al. [22] for the HRF dataset. It is observed that model accuracy depends on the quality of the image datasets.

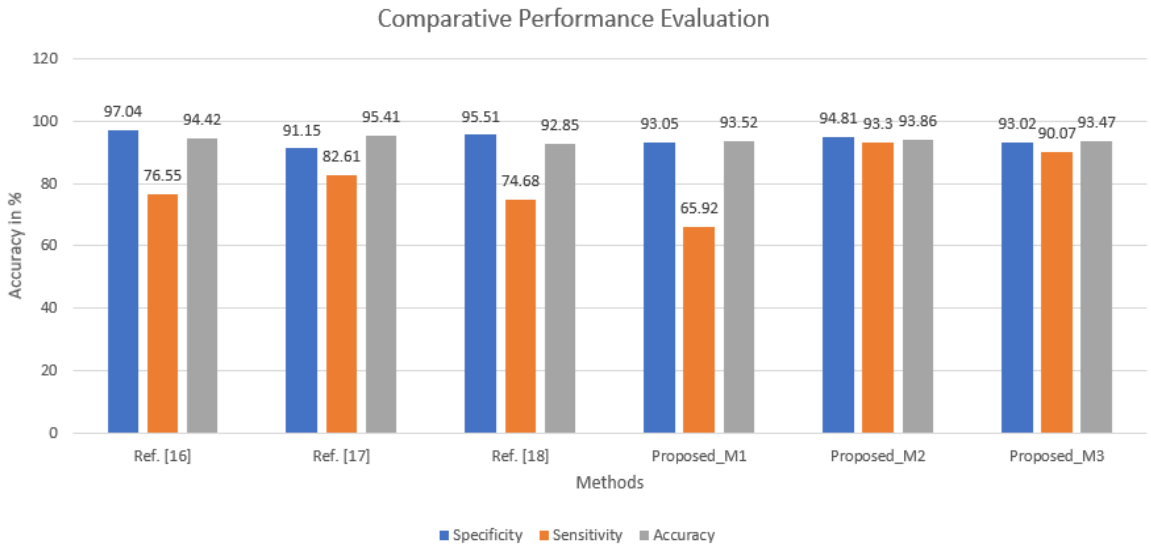

Fig. 11. Performance evaluation of proposed model with previous research for DRIVE dataset.

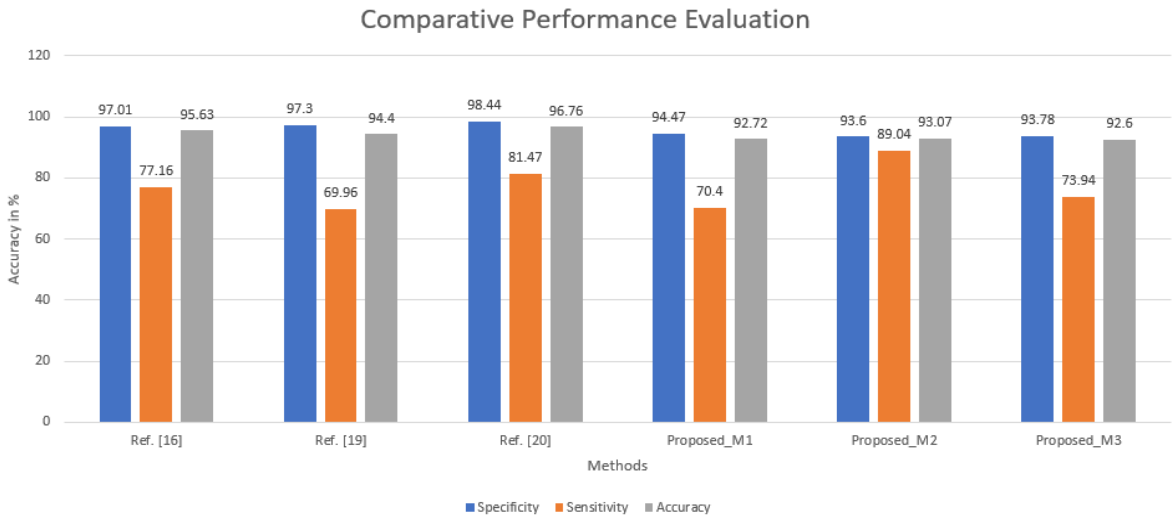

Fig. 12. Performance evaluation of proposed model with previous research for STARE dataset

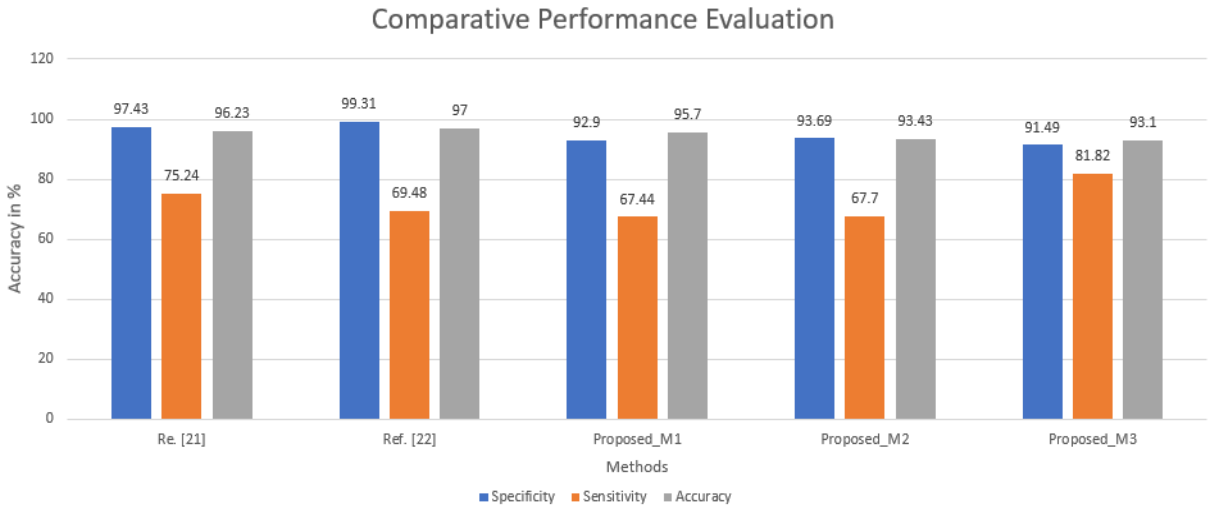

Fig. 13. Performance evaluation of proposed model with previous research for HRF dataset

5. Conclusion and Future Scope

In this paper, proposed the deep learning models based on modified U-net architecture for retinal image segmentation. Firstly, perform the image augmentation with the help of various hypermeters and reduces the error rate. Then augmented images are fed to the proposed model where the U-net architecture is improved by using the residual connection and Adam optimizer. The script-based approach is used for blood vessel segmentation. Finally, we compare the performance of the three models on DRIVE, STARE, and HRF datasets. For performance evaluation of the models, measure the sensitivity, specificity, and accuracy parameters. It is observed that more thin blood vessels are segmented on the retinal image in the HRF dataset using model-3. And also, it is observed that model-2 gives a good result for DRIVE and STARE datasets. It has been found that encoder and decoder layers give more significant results when extended in the basic U-net model. We've noticed that while the proposed retinal image segmentations effectiveness generally marginally improves on the sensitivity parameter for preprocessed retinal image datasets, it only significantly decreases on a few other parameters. It is evident that a trade-off exists. The outcomes have demonstrated that the proposed models are also capable of making accurate forecasts without any prior processing. The limitation of this research, if there is a blurred retinal image fed to the proposed model then the performance of the models is degraded. Future work could be used more hyperparameters and increase the convolutional layers of the network for improving the accuracy level.

Appendix A Appendix Title

Appendixes, if needed, are numbered by A, B, C... Use two spaces before APPENDIX TITLE.

Acknowledgment

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