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Impact of Image Enhancement Technique on CNN Model for Retinal Blood Vessels Segmentation

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ABSTRACT In this paper, we have developed a new method of accurate detection of retinal blood vessels based on a deep convolutional neural network (CNN) model. This method plays an important role in the observation of many eye diseases. Retinal Images have many issues that make the process of vessels segmentation very hard. We treat each issue of the retina image with the greatest observation to obtain a well-segmented image. The first step is to apply a pre-processing method based on fuzzy logic and image processing tactics. In a second step, in order to generate the segmented images, we propose a strided encoder-decoder CNN model. This network is trained and optimized using the Dice Loss function that supports the class imbalance problem that is in the database. The proposed model has a U-Net shape, but it is deeper and the pooling layers are replaced with strided convolutional layers in the encoder. This modification allows for a more precise segmentation of vessels and accelerates the training process. The last step is post-processing for removing the noisy pixels as well as the shadow of the optic disc. The performance of the proposed method was evaluated on DRIVE and STARE databases. The proposed method gives a sensitivity of **0.802** and **0.801** respectively on DRIVE and STARE, with an accuracy of **0.959** and **0.961** respectively. We focused on sensitivity and accuracy measurements that represent the accuracy of the model, especially tiny vessels. According to the results, the model outperforms many other proposed methods, especially in the above-mentioned measures.

INDEX TERMS Retinal, segmentation, vessels, morphological operation, CLAHE, FCM.

I. INTRODUCTION

Fundus analysis is essential for the early detection of eye diseases. The diagnosis of eye disease related to the digital image of the color fundus image is mainly observed from the segmentation of its vessels. Diseases such as diabetes, hypertension and arteriosclerosis affect the human retina due to alteration or deterioration of the blood vessels [1], [2]. The appropriate analysis of blood vessels or their modifications can be segmented using the image segmentation method.

The automatic segmentation of the retinal blood vessels plays an important role in the analysis of the disease as quickly as possible for further treatment. There are many methods of segmentation proposed by different researchers based on image processing techniques and machine learning techniques [3], [4]. These methods are based on image filtering techniques such as Gabor Wavelet's filter, Wiener's filter and other filtering techniques [5]. Wiener filters based on morphological operators are also used for the extraction of retinal blood vessels [6]. Morphological operations were used to remove the non-uniform [7].

In this research paper, a new methodology for the extraction of blood vessels is proposed. It contained a fuzzy

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logic-based image enhancement technique with a deep learning model for obtaining quality vessel images. First, we apply the pre-processing method based on Fuzzy logic and image processing tactics. In a second step, in order to generate the segmented images, we propose a fully strided-CNN model to segment the retinal vessels from the preprocessed images. This network is trained using the Dice Loss function that supports the class imbalance problem that is in the database. The proposed model has a U-Net shape, but it is deeper and we replace the pooling layers in the encoder part with strided convolutional layers. This modification allows more precise segmentation of vessels and speeds up the training process. The generated output image has the same resolution as the input image. It's an image-to-image problem solved by the proposed CNN model. By using the Dice Loss function for training, CNN will not get stuck in the local minima because of the class imbalance problem. It will balance the foreground pixels (vessels pixels) and the background pixels. The last step is the post-processing to remove the noisy pixels as well as the shadow of the optic disc. The contributions are summarized as follows:

1) A pre-processing step is proposed to eliminate the illumination in the retinal images and improve the contrast variation.
2) The CNN model has a U-Net form, but it is a deeper encoder-decoder model and the pooling layers of the encoder part are replaced by strided convolutional layers.
3) To solve the class imbalance problem found in the training database, we use the dice loss function to train the CNN and optimize the weights to overcome this problem.

Following, the related work is discussed in Section II. The pre-processing step and the proposed CNN model along with the loss function are explained in Section III. The implementation details, the databases and the evaluation parameters are described in Section IV. The quantitative and qualitative results are discussed in Section V. Section VI presents the conclusion and future work.

II. RELATE WORKS

There are many segmentation techniques published in the literature. They can be divided into supervised and unsupervised methods.

Supervised techniques require initial information about segmented retinal blood vessels. The performance of the supervised methods is much better than unsupervised methods. However, getting the required information such as expert training sampling datasets for a supervised segmentation process can sometimes be difficult. The main disadvantage of the supervised method during vessels segmentation is the classification of vessels and the background pixels considered tedious. Niemeijer *et al.* [8] have developed the supervised classification of pixels for retinal segmentation. Each pixel of a green channel of the retinal images was used to generate the feature vector, and a k-NN classifier is used to drive the feature vector. Staal *et al.* [9] developed the supervised segmentation method using the edge extraction method. Primitives in the form of line elements were generated from the ridge and feature vectors were used for each pixel for the classification process as vessels and background using the selection sequential entities ahead and k-NN. Soares *et al.* [10] created feature vectors composed of pixel intensities with scaled responses from the two-dimensional Gabor wavelet transform on each pixel. The resulting feature vector was classified into vessel and non-vessel pixels using a Bayesian classifier and Gaussian mixtures. Fraz *et al.* [11] have developed the supervised segmentation method based on the ensemble classifier using bootstrapped decision trees for the extraction of retinal blood vessels. Lupascu *et al.* [12] presented a supervised method of extraction of retinal vessels using an Ada-Boost classifier. Ricci and Perfetti [13] have implemented two different methods of automated vessels segmentation, based on the detection of vessels line operators by the classification of the support vector machine. Cemal [14] has developed a hybrid method of extracting retinal blood vessels by combining Circular and Naive Bayes. The circular method is used to sample pixels along with the magnification of the circles centred on the current pixels. Then, after the classifier Naive Bayes, the pixel is classified as ship or non-ship.

The unsupervised segmentation is an arduous task to achieve accurate segmentation of retinal blood vessels due to the pixel-based classification of vessels and non-vessels. Many unsupervised methods previously proposed are quick in the computation process, but they are not capable of correctly detecting vessels and non-vessels due to retinal network limitation of unconnected vessels of the fundus image. As a result, these methods make it possible to obtain less sensitivity and precision. Chaudhuri *et al.* [3] developed the unsupervised vessel extraction method on the basis of the matched filter using the approximate intensity of the greyscale profiles of the cross-section of the retinal vessels along with the curve form of Gauss. But the detection sensitivity of vessels is very low. Hoover *et al.* [4] developed the retinal blood vessel extraction method using a thresholding technique combining local vessel characteristics and region-based features on matched filter response (MFR) image. Martinez-Perez *et al.* [15] applied a space-scale analysis with the growing region for the segmentation of retinal vessels. The novelty of this method is to detect large vessels, but otherwise, this method does not detect tiny vessels. Zana and Klein [16] have developed the mathematical morphological method for the retinal blood vessel segmentation; they have achieved a very good result, but the structure of the vascular network is not always connected. Jiang and Mojon [17] used an adaptive local thresholding model using a multi-threshold approach verification based on segment blood vessels in the retina. The technique envisioned in [17] was confronted with the limits of some unconnected vascular structures and the inability to detect the thinnest vessels. Vlachos and Dermatas [18] implemented their method

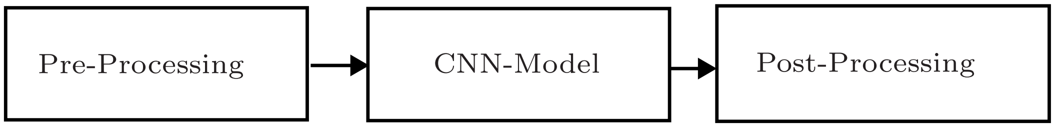


FIGURE 1. The proposed pipeline for retinal vessels segmentation.

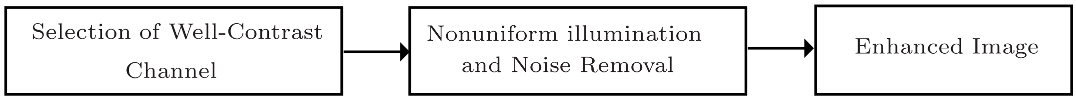


FIGURE 2. The proposed pre-processing stages.

by combining a multi-scale line tracking procedure and a morphological post-treatment for the segmentation of retinal vessels. But this technique also did not detect small vessels. The method developed by Wang *et al.* [19] combined the multi-wavelet and multi-scale hierarchical decomposition for the segmentation of retinal vessels. The method has reached the highest precision, and its calculation is expensive. Mendonca and Campilho [20] implemented the process by combining differential filters for centre line extraction with operators for the detection of the retinal vessel network. The good performance is achieved, but the calculation is expensive. Xiao *et al.* [21] produced a spatially constrained Bayesian technique with the level defined for the segmentation of retinal vessels.

Tolias and Panas [22] used a fuzzy C-means algorithm to detect blood vessels in the retinal segment from images of angiograms images, but the technique did not segment the thinner vessels because of their low contrast against the background. Kande *et al.* [23] combined the paired filter and a space-weighted fuzzy c-means for vessel extraction of retinal fundus images. But tiny vessels cannot be extracted by the low contrast of the vessels. Yang *et al.* [24] proposed a hybrid method combining Fuzzy C-Mean and morphological operations. But the algorithm has been tested by visual comparison, by visual calculation of the sensitivity level of the detection of small vessels cannot be calculated. In this research paper, a new supervised method is implemented, taking into account the above-mentioned limitation, to detect tiny blood vessels and perform better than the existing supervised methods.

A. SEGMENTATION USING CNN

Semantic segmentation and labeling have a wide range of applications such as scene comprehension, autonomous driving and robotics. Nowadays, pixel-wise segmentation is an active research problem due to the emergence of some challenging datasets. Pixel segmentation is the process of labeling each pixel with the correct class and then fusing pixels with similar tags in a region. Different methods have been proposed before the arrival of deep networks. These methods were mainly based on the extraction of hand-crafted features. The extracted features have been classified using clustering methods or classifiers such as Random Forest. After the successful methods of deep learning in object classification task, researchers began to exploit the learning capabilities of CNN's features to solve the problem of segmentation. They are also trying to adjust the object classification networks and apply them to the problem of segmentation. A Fully Convolutional Network (FCN) [25] has been proposed to solve the problem of segmentation. This is a fully convolutional model without the need to use the fully connected layers used in the classification tasks. The strength of this architecture lies in the fact that it has a variable input image resolution and a remodeling of the final output to generate the segmented image. The idea of the encoder-decoder model has been introduced in the U-net [26] for the segmentation of medical images. This architecture extracts the characteristics of the encoder part and then reconstructs the segmented image in the decoder part. Skip connections were used to transfer some extracted details from the encoder to the decoder. As a summary, CNN models show impressive performance in solving the segmentation task and there is still room for improvement to generate more accurate segmentation results.

III. THE PROPOSED METHOD

A. PROBLEM STATEMENT

The computerized segmentation methods of retinal vessels have received increasing attention in recent years, after the introduction of deep learning to solve computer vision and image processing problems as shown in Figure 1. In the case of a retinal image X, the task is to classify each pixel in X as a vessel or a non-vessel pixel. Our approach is, therefore, an image-to-image problem which involves inserting the input image X and generating the segmented vessels image as an output.

B. PRE-PROCESSING

During a pre-processing stage, we propose an image enhancement technique for vessels enhancement. The pre-processing steps are illustrated in Figure 2. The purpose of applying the pre-processing steps on the training data is to suppress the irregular illumination in the images and to improve the low and varying contrasts. The first step is to select the well-contrasted RGB channel and the second step is to remove the non-uniform illumination with a morphological operation and eliminate the noise with a fuzzy C-Mean. The last step is to use CLAHE to get a well-contrasted image. The combination of these sequential steps is known as the proposed image enhancement technique.

1) SELECTION OF WELL CONTRAST RETINAL CHANNEL

The retinal color fundus images process as input images for our proposed retinal vessel segmentation algorithm. They are monochrome and the available databases contain such types of color retinal fundus images and most of these images are captured using fundus cameras in hospitals. Color retinal images have three channels, namely: the red, green and blue channels. Each channel gives some sort of information. The red channel includes both luminance and contained noise. The green channel has the least noise and allows a good observation of vessels compared to red and blue. The blue channel contained both shade and noise.

The main requirement is to process the images more efficiently and make the data more relevant to the training process. The grayscale representation is used to extract the descriptors instead of operating directly on the color images. The main reason for using grayscale representation because of the reduced computational requirements. Indeed, color information has limited advantages in many image processing applications, including ship segmentation. Color images process unnecessary information that can increase the amount of processing data needed to achieve the desired performance [27].

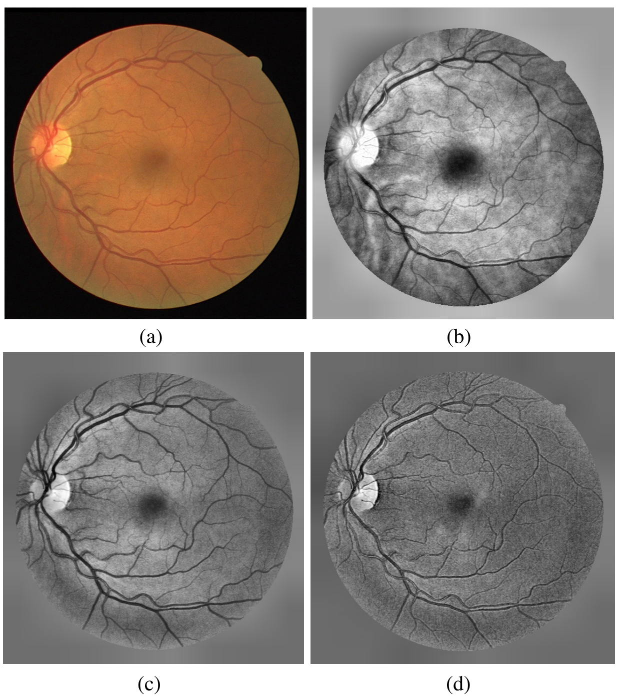


FIGURE 3. Selection of suitable channel from retinal fundus image. (a) Color Retinal image, (b) Grey representation of Red channel, (b) Grey representation of Green channel, (c) Grey representation of Blue channel.

In order to obtain an appropriate input image for the processing of each color channel, the defined processing method is used to convert the color retinal fundus image to greyscale format for further processing, as shown in Figure 3. As the blood vessels appear with good contrast in the green channel than the red and blue channels. We selected the green channel for further processing and training treatment. The selection of the green channel is verified in several research works [9], [17], [20] for the segmentation of the retinal blood vessels.

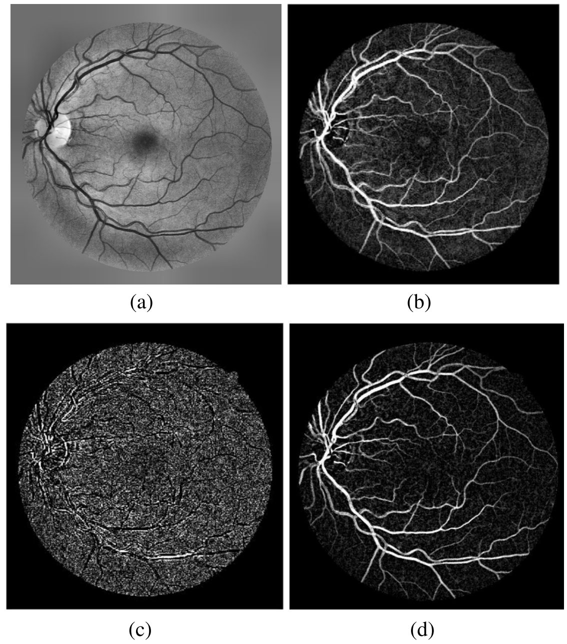


FIGURE 4. Background normalization: (a) Green channel. (b) Top hat image. (c) Bottom hat image. (d) Tophat-bottomhat image.

2) BACKGROUND HOMEGENIZATION

After the grayscale representation, our next task is to analyse the pixels in the background of the retinal image to obtain a uniform contrast in blood vessels against their background. The background of the retinal fundus image contains variations in the intensity level. Because of this variation in intensities, different contrasts occur in different regions of the image that make it difficult to observe the vessels and it becomes more difficult to visualise the tiny vessels. The background changes must be uniform so that the vessels can be visualized properly for successful training and segmentation of the retinal blood vessels. For this task, we use morphological operations, namely top hat transform and bottom hat transform. A top-hat transformation is performed by subtracting the opening of the original image from the image itself. The L line structuring element is used for the success of morphological operations. We used the bottom-hat operation to standardize the intensity level by reducing the noise, as shown in Figure 4. The main advantages of using top-hat and bottom-hat operations are the contrast enhancement of tiny or low contrast vessels compared to their background. But there is still noise that makes it difficult to analyse normal vessels and more difficult to analyse tiny vessels. To solve this problem, we use Fuzzy C-mean to suppress background noise to better observe normal vessels, as well as tiny or low-contrast vessels.

C. FUZZY C-MEAN MODEL FOR SEGMENTATION OF BLOOD VESSELS

Fuzzy segmentation is implemented to obtain initial retinal blood vessels without noise as well as with well-adjusted contrast. For this purpose, we used Fuzzy C-means (FCM) classification method to generate an initial representation of a retinal vascular network with the maintenance of retinal vessel retentive homogeneity. FCM allows pixels of several classes with a membership function level between 0 and 1. The cluster centre is calculated in the FCM algorithm by a dissimilarity function using an iterative approach. By updating the cluster centres and the membership of each pixel, FCM then moves the cluster centres to the actual location in a set of pixels. In the case of retinal vessels, the FCM is used to identify the actual pixels of the retinal vessels. This pre-processing helps the CNN model and post-processing steps to segment the retinal blood vessels properly with uniform contrast as well as without noise, allowing for accurate segmentation of the retinal blood vessels. The FCM model of the retinal blood vessel is developed:

Fuzzy partitioning is introduced by considering the membership function and clusters. The membership matrix is first arbitrarily initialized. Let $U = [u_{im}]$ matrix whose elements are memberships of x_t in cluster n, $x_t = x_{t_1}, x_{t_2}, x_{t_3} \ldots .x_{t_n}$. The Fuzzy C partition space for the retinal image X is the set of matrices U as presented in the equation 1.

$$\sum_{i=1}^{c} u_{im} = 1, \quad 1 \leq m \leq c. \tag{1}$$

The performance index parameter of the membership matrix U and C_n is taken into account in FCM, as shown in the equation 2.

$$M(U, Cn) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} \sum_{m=1}^{c} {u_{im}}^k {d_{im}}^2. \tag{2}$$

U presents the membership matrix and an index of the membership matrix u_{im} is between 0 and 1. C_i is considered as cluster center, d_{im} is the Euclidean distance between the center of i^{th} center (C_i) and the data point j^{th}. k in $[1, \infty]$ is a weighting exponent. The main task is to reach the minimum dissimilarity function, it can be performed with two conditions [28] as shown below Equations 3 and 4.

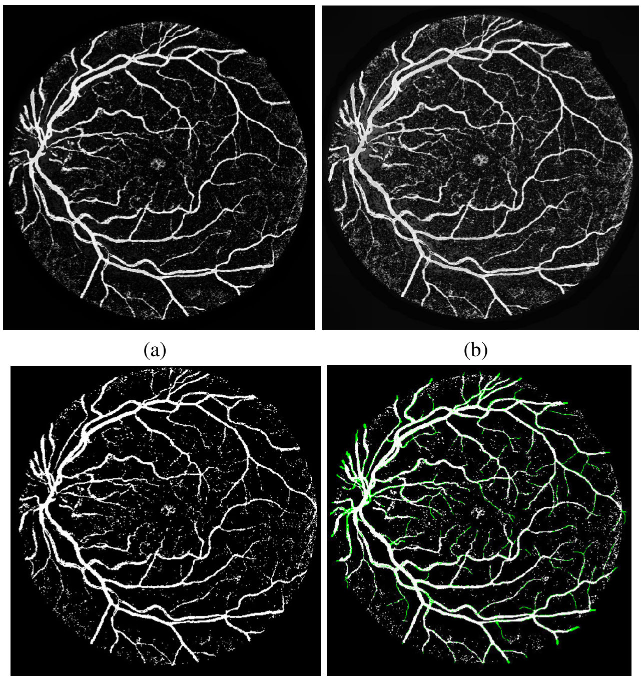
$$C_i = \frac{\sum_{j=1}^{n} {u_{im}}^k x_j}{\sum_{j=1}^{n} {u_{im}}^k} \tag{3}$$

$$u_{im} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{im}}{d_{km}}\right)^{2/(m-1)}}. \tag{4}$$

The FCM algorithm is explained in the following steps.

1) The U membership functions contained in the constraint, as shown in the equation 1, are randomly initialized.
2) The centres C_i are calculated by applying the equation 3
3) The dissimilarity between the centre and the data point is calculated by applying the equation 2. It will stop if its improvement over the previous iteration is below the threshold.
4) An updated membership function U is computed using the equation 4.

Figure 5 shows the output of FCM. It is observed that the images initially contained uniform contrast with noise as well, but that the retinal blood vessels are more visible and the noise is reduced after updating the members. It should be noted that the image is still not ready to be used for training the CNN and obtain a well-segmented image. To further improve the vessels contrast, especially small vessels can be visualised, CLAHE is used to obtain a satisfactory contrast image. The output image of CLAHE is shown in Figure 5(c), and we can observe the low contrast vessels also with.



(a) (b) (c) (d)

FIGURE 5. Output of FCM Model for Segmentation of Retinal Blood Vessels(a) Initially Output of Fuzzy image (b) Final Fuzzy Image Output (c) CLAHE Output Image (b)Initial Vessels observation especially low contrast vessels.

D. CNN ARCHITECTURE

To effectively use the preprocessed dataset for retinal vessels segmentation, we propose a deep modified U-Net [26] model with some additional layers to generate the segmented vessels image as shown in Figure 6. The network has two parts; an encoder part and a decoder part. The encoder extracts the features that represent the input image, and the decoder uses these features and reconstructs the output as a segmented vessels image. To exploit the extracted features in the encoder for better segmented vessels and to extract the tiny vessels, skip

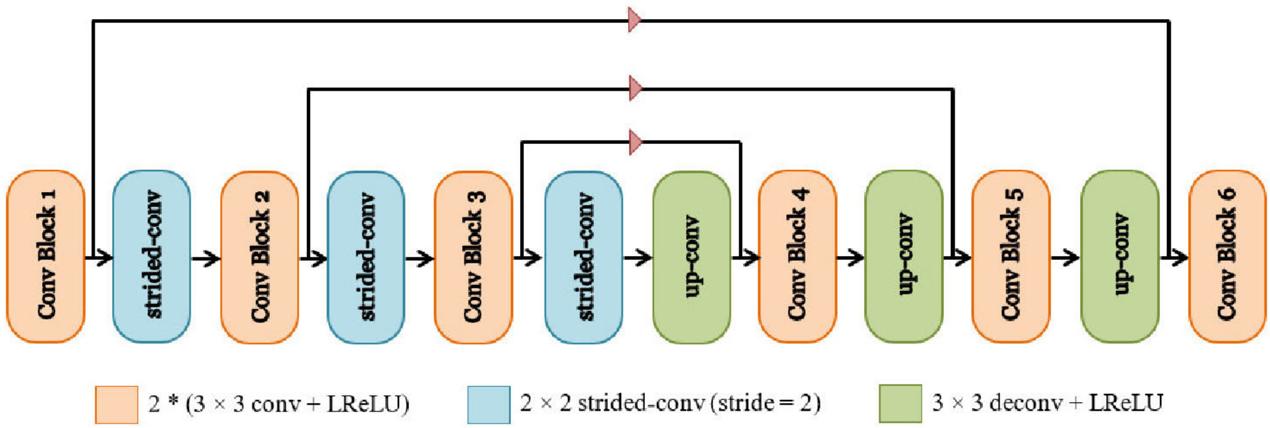


FIGURE 6. The proposed CNN model. Each convolutional block consists of two convolutional layers followed by LReLU. Strided-convs are used to decrease the resolution of the features in the encoder. Up-convolutional layers are used to increase the resolution of the features in the decoder. Skip connections and concatenation layers are used in the decoder to concatenate and fuse the features from the encoder and the decoder. This generates better segmented image with sharper vessels edges.

connections transfer the detailed features from the encoder to the decoder. The encoder part comprises three convolutional blocks; each block has two convolutional layers followed by LReLU as an activation function. After each conv block, a strided convolutional layer [29] is used to decrease the feature resolution and to accelerate the training process.

The decoder has almost the same architecture as the encoder, but with task-specific layers. It consists of three convolutional blocks, and deconvolutional layers are used before each block to increase the resolution of the features and reconstruct the segmented image. For more accurate segmentation and sharper vessels edges, the extracted features in the encoder are exploited to improve the segmentation output. Features from the encoder are transferred to the decoder using skip connections and concatenated with the corresponding features from the decoder. They are concatenated and fused using a convolutional layer of 1 × 1 kernel size. The segmented image is generated by a soft-max layer, where the output image has 2 channels as a probability map of the foreground (vessels pixels) and the background.

The proposed model is different from the original U-Net. The output resolution is smaller than the input resolution in the original U-Net but our proposed model preserves the same resolution for the output as the input. To downsample the features in the encoder, U-Net uses max-pooling layers which take the maximum value in a window. Max-pooling layers miss the spatial information of the extracted features which are important in the segmentation task. We proposed to use the strided convolutional layers instead of max-pooling layers to downsample the features. Strided convolutional layers are trainable layers and have the property of preserving the spatial information for the features. This enhances the segmentation task and helps in detecting the tiny vessels.

E. LOSS FUNCTION

The quality of the segmented retinal vessels using the proposed CNN not only depends on the architecture choice but depends also on the loss function that is selected to train the model and optimize the network parameters. The ground-truth of the retinal vessels images suffers from class imbalance. That is, we have two classes to be segmented; the foreground (vessels) and the background. The class distribution of the foreground and the background is imbalanced. It is clearly observed that almost 90% of the ground-truth pixels belong to the background class and 10% of the pixels belong to the foreground class (vessels pixels). Ignoring the class imbalance problem during training results in sub-optimal performance. To overcome this issue, Dice Loss function [30] is selected to train the proposed model. It is defined as:

$$L_{dice} = 1 - \frac{2\sum_{x\in\Omega} p_l(x) g_l(x)}{\sum_{x\in\Omega} p_l^2(x) + \sum_{x\in\Omega} g_l^2(x)}. \tag{5}$$

where $p_l(x)$ is the probability of the pixel x to have the label l. $g_l(x)$ is the ground-truth label as a vector where it is 1 for the true class label and 0 for the other classes.

F. POST-PROCESSING

The output image of the CNN model contained noisy pixels, making it difficult to analyse small vessels. We use the morphological reconstruction operation based on a double threshold method. The morphological reconstruction operation generates the final binary image and is based on marker and mask images. We generate the mask and marker images from the histogram of the image as shown in Figure 7. The mask image (as shown in Figure 8(a)) is obtained by applying the threshold to the median value of the image based on the histogram. While the marker (as shown in Figure 8(b))) is obtained by applying the threshold as a multiple of 0.6 standard deviation subtracted from the median value of the image histogram. After making the mask and marker image, we apply the morphological reconstruction to obtain the binary image of the retinal vessels (as shown in Figure 8(c))). To obtain an accurate vessels image, we apply image

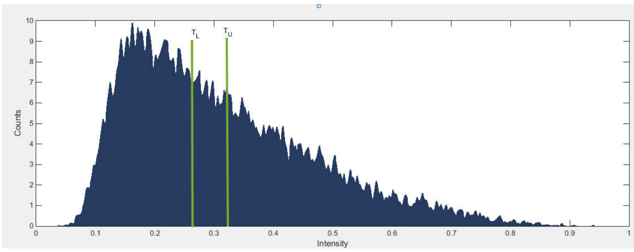
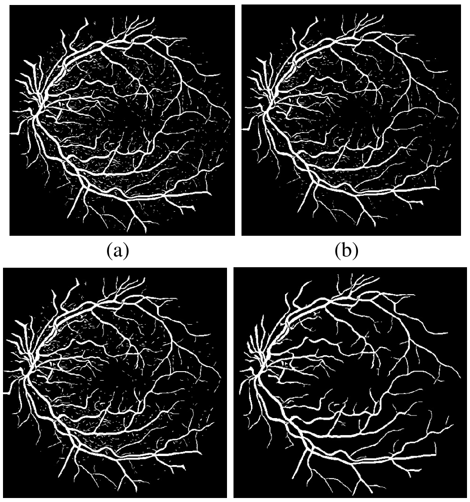


FIGURE 7. **The histogram designated two thresholds as two vertical bars. The T_L is obtained by using the median value of edge-based histogram, whereas T_U is obtained by using as a multiple of 0.6 standard deviation subtracted from the median value of the image histogram.**



(a) (b) (c) (d)

FIGURE 8. **The post-processing process. Fig(a) shows the mask image, Fig(b) marker image, Fig(c) shows morphologically reconstructed image and Fig(d) shows the final binary image of retinal blood vessels.**

processing tactics to remove small objects from the binary image and give an accurate vessels image. Because the morphologically reconstructed process results in some isolated noise segments pixels being detected as false vessels. Post-processing is performed to remove small objects from the reconstruction image to contain only well-connected vessels in the image. For this task, the small areas less than 50 pixels are removed to get the final binary image (as shown in Figure 8(d)).

IV. DATABASES AND MEASURING PARAMETERS

This section presents the implementation details of the proposed CNN model, the databases used for training and testing the model and the measurement parameters used for computing the method performance.

A. DIAGNOSTIC PROBLEM AND DATA

The observation condition of the human vascular system is an important diagnostic parameter in many medical conditions like analysis of retinal blood vessels to diagnose eye disease such as diabetic retinopathy. A blip of blood vessels in the retina has a very severe impact on the quality of vision. Currently, the most common reason for such abnormalities is diabetes, which according to the American diabetes association has 9.3 percent incidence in the US in 2012, and it predicts to rise. As results of eye disease progression such as diabetic retinopathy that affects over a quarter of adults, it is currently the most common cause of vision loss in the developing countries.

There are numerous medical imaging modalities for assessing the conditions of the retinal vascular system, including fundus imaging, fluorescein angiography, and OCT (optical coherence tomography) angiography. In this research work, we consider fundus imaging. Fundus imaging is the process of taking an image of the back of the eye in the visible band. The segmentation of retinal blood vessels in this modality is subjected to background explained in the introduction and related work sections.

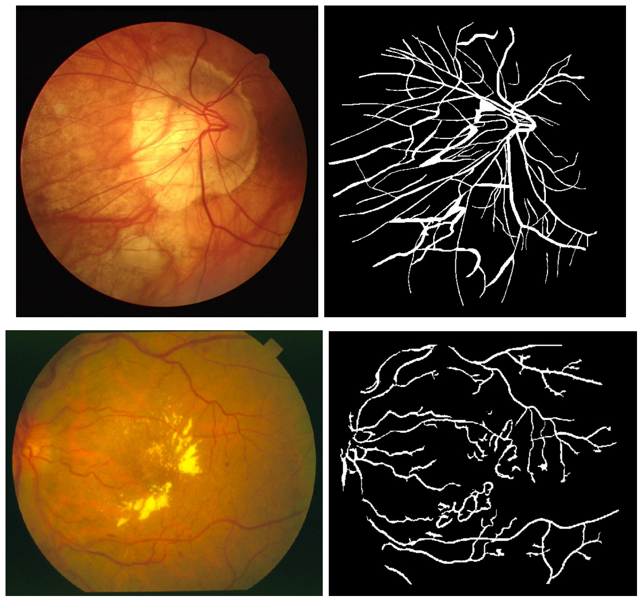


FIGURE 9. **Training images from DRIVE (top) and STARE (bottom) databases and the corresponding manual segmentation.**

In image processing, computer vision and pattern recognition terms, detection of retinal blood vessels is a highly demanding segmentation task, where the objective is to extract the structure of interest (blood vessels) from the background of the image. The input is the retinal image and the output is the segmented vessels. In experimental results, we depend mostly on two publicly available databases, DRIVE [9] and STARE [4], which are mostly used from 34 years of study for the segmentation of retinal blood vessels. Using these databases gives the chance to compare with other methods. DRIVE database contains 40 images split equally into training and testing sets. The corresponding ground truth image (binary segmented image) is available for each image of this database. The STARE database contains 20 images and is divided into two groups called training and picture sets. 50% of the images in this database contain pathologies and central light reflex issues that make this database a challenging database for segmenting retinal blood vessels. Figure 9 shows the DRIVE (top) and STARE (bottom) images along with their manual segmentation images.

B. CNN IMPLEMENTATION DETAILS

MatConvNet [31], a MATLAB toolkit implementing CNNs for computer vision applications, is used to implement the network and measure the model performance. The network parameters are initialized using the Xavier initialization method [32]. Stochastic gradient descent (SGD) is used to train the model and update the weights with the following settings: the weight decay is set to 10^{-5} and the momentum to 0.9. The learning rate is set to 10^{-3} and decrease it when the validation error does not change. The model is trained from scratch and the training process is stopped when there is no change in the loss function values.

With respect to the training data, the available datasets have a small number of images for training (20 images from DRIVE dataset and 10 images from STARE dataset). To overcome this issue, we apply data augmentation on the training images. From each training image, small patches were extracted to increase the training set. A sliding window, which has half resolution of the original image, was passed through the entire image to extract overlapped patches. We also apply the same process on the ground-truth images so that we have correspondence ground-truth of the extracted patches. So, the extracted patches cover the whole image regions. The generated patches area combined with the original full images and 90% of the images is used for training and the remaining is used for validation. The mean is subtracted from the training set. The final training set contains complete images and the extracted patches so the network learns to see different patches of the input images. We applied the preprocessing step on the original images before extracting the patches and then the mean is subtracted from them.

C. MEASURING PARAMETERS

Four parameters are used to validate the performance of the proposed method. These parameters are Sensitivity (Se), Specificity (Sp), Accuracy (Ac) and Area Under Curve (AUC). The calculation of these parameters is given below.

$$\text{Sensitivity} = \frac{TP}{TP + FN}. \tag{6}$$

$$\text{Specificity} = \frac{TN}{TN + FP}. \tag{7}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN}. \tag{8}$$

$$\text{AUC} = \frac{Se + Sp}{2}. \tag{9}$$

V. RESULTS AND DISCUSSION

This section presents the performance of the proposed methods on the databases and the impact of the pre-processing and post-processing steps. We also analysed the performance of our proposed method on challenging images of the two databases. We performed a comparative analysis of the performance of our methods with existing methods.

TABLE 1. Analysis of performance on databases.

Database	Se	Sp	AC	AUC
DRIVE	0.802	0.974	0.959	0.948
STARE	0.801	0.969	0.961	0.945

A. PERFORMANCE ON DRIVE AND STARE DATABASES

The performance analysis of our method is presented in Table 1. Our method reached the accuracy of 0.959 on the DRIVE database and 0.961 on the STARE database and the sensitivity around 0.80 on both databases. It is clearly shown that the proposed method can be used to segment the vessels as compared to manual segmentation. Figure 10 shows the qualitative results of the proposed method on test images form both databases. It is clearly shown that the proposed model managed to segment the tiny vessels and the segmented output image is comparable with the corresponding ground-truth.

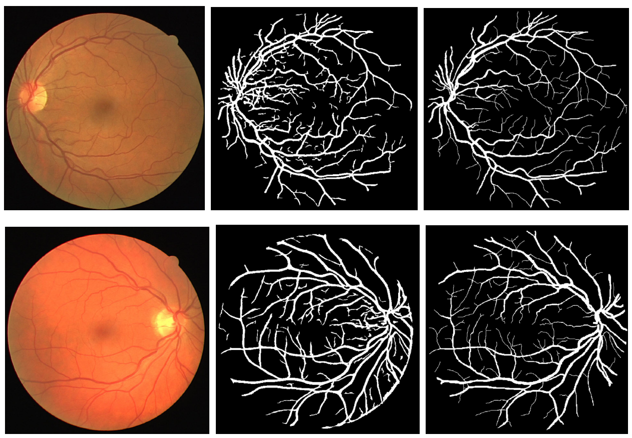


FIGURE 10. Final output images of the proposed method. From left to right: input image, output image, corresponding ground-truth. Top: DRIVE image, bottom: STARE image.

B. IMPACT OF THE PRE-PROCESSING AND POST-PROCESSING STEPS ON THE RESULTS

To check the usefulness of the pre-processing steps on the training process, the proposed model was trained with and without pre-processed training images. As reported in Table 2, the pre-processing steps improve the training process and the performance of the proposed model outperforms the model trained without the preprocessing steps. The pre-processing steps eliminate the uneven illumination, reduce the noise, and generate pre-processed images with better contrast which helps to produce well-segmented output images.

Moreover, Table 2 reports the importance of using the post-processing steps. The post-processing steps improve the final vessels image and the performance of the proposed model

TABLE 2. Impact of pre & post processing steps.

Method	without Pre-Processing			without Post-Processing			with Pre & Post Processing		
Database	*Se*	*Sp*	*AC*	*Se*	*Sp*	*AC*	*Se*	*Sp*	*AC*
DRIVE	0.631	0.663	0.646	0.773	0.941	0.932	**0.802**	**0.974**	**0.959**
STARE	0.629	0.661	0.638	0.782	0.953	0.937	**0.801**	**0.969**	**0.961**

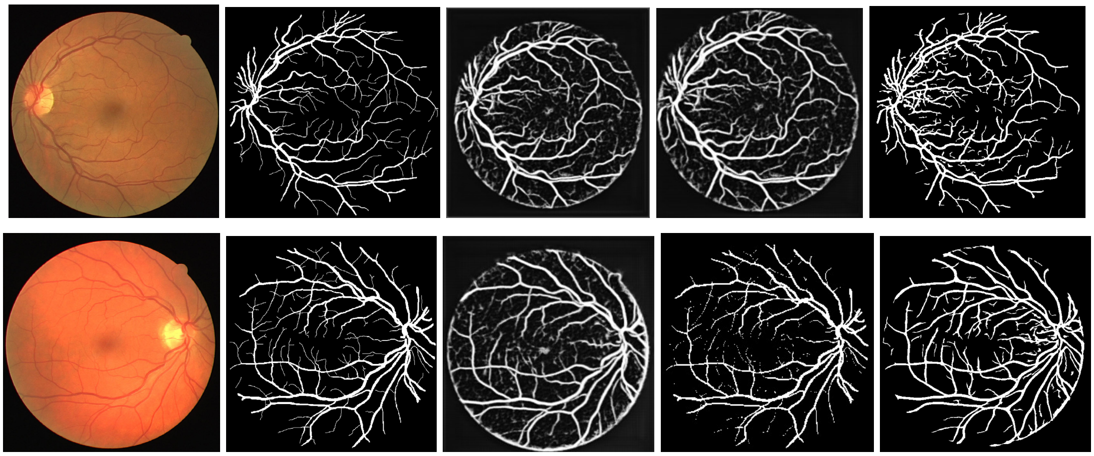


FIGURE 11. Comparison of proposed output images with [33], [34] especially tiny vessels. First column represents original image and second coloum represent ground truth images, third column shows output image of [33], fourth column shows output image of [34] and fifth column shows proposed method output image.

gives better-segmented images than without post-processing the CNN output. The post-processing steps remove noisy pixels and give better observation of tiny vessels.

C. PERFORMANCE ON CHALLENGING IMAGES

There are 50% abnormal images containing abnormalities in both databases, and the presence of abnormalities makes it difficult to accurately segment the retinal blood vessels. We named these images as challenging images. We calculated the performance of the proposed method on these challenging images and obtained better performance, as shown in Table 3. The performance obtained on difficult images is proof of the ability of our method to accurately detect the retinal blood vessels.

TABLE 3. Analysis of performance on challenging images.

Database	*Se*	*Sp*	*Ac*	*AUC*
DRIVE	0.791	0.961	0.951	0.937
STARE	0.789	0.962	0.956	0.941

D. COMPARISON WITH OTHER CNN-BASED METHODS

For further validation, we compared our proposed CNN-based method with other existing retinal vessel-based segmentation methods based on CNN, as shown in Table 4. Our method outperforms other methods in terms of accuracy in the DRIVE and STARE databases. In terms of sensitivity, our method also outperforms other CNN-based methods (as shown in Table 4) for retinal blood vessels. In addition, we performed a comparative analysis of our method, which focuses on the detection of tiny vessels. The detection of tiny vessels is analysed on the improvement of the sensitivity. The proposed method, compared to the method recently implemented, concerns the problem of tiny vessels like [33], [34] as shown in Figure 11, from Table 4, and allows us to observe that we have obtained better performances that [33], [34]. This shows that our proposed method has the ability to detect more tiny vessels. Our method is more robust in terms of execution time and few researchers have indicated the execution time shown in Table 4, and our method runs in less time to give a segmented image compared to others reported runtime methods.

E. COMPARISON WITH EXISTING METHODS

For further comparative analysis, we compare the performance of our method to other existing retinal blood vessel segmentation methods in the STARE and DRIVE databases. Table 5 shows the results of the comparison. It is observed that the proposed method offers an accuracy compared with Thangaraj and al [51] based on DRIVE data and outperform accuracy that obtained with other methods, and that the proposed method has higher accuracy against Thangaraj *et al.* [51] on the STARE database. We also compared the sensitivity parameter of the proposed method with other existing methods. We obtained a higher sensitivity

TABLE 4. Comparison of proposed segmentation methods with CNN-based learning methods.

Database	DRIVE					STARE				
Methods	$Time$	Se	Sp	AC	AUC	$Time$	Se	Sp	AC	AUC
Zhang et al [35]	20s	-	-	0.940	-	-	-	-	-	-
Maj et al [36]	-	-	-	0.947	-	-	-	-	-	-
Liskowski et al [37]	-	-	-	0.949	0.973	-	-	-	0.949	0.982
Fu et al [38]	-	0.760	-	0.952	-	-	0.741	-	0.958	-
Wu et al [39]	-	-	-	-	0.97	-	-	-	-	-
Yao et al [40]	-	0.773	0.960	0.936	-	-	-	-	-	-
Maninis et al [41]	90s	-	-	-	0.822	-	-	-	-	0.831
Fu et al [42]	1.3s	0.729	-	0.947	-	-	0.714	-	0.954	-
Tran et al [43]	-	0.753	0.969	0.926	-	-	-	-	-	-
M et al [44]	-	0.660	0.985	0.956	-	-	-	-	-	-
Song et al [45]	0.750	0.979	0.949	-	-	-	-	-	-	
Soomro et al [33]	-	0.746	0.917	0.948	0.831	-	0.748	0.922	0.947	0.835
Guo et al [46]	-	-	-	-	0.965	-	-	-	-	-
Guo et al [47]	-	-	-	-	0.973	-	-	-	-	-
Brancati et al [48]	-	0.742	0.982	0.954	-	-	-	-	-	-
Yan et al [49]	-	0.765	0.981	0.954	0.975	-	0.758	0.984	0.961	0.981
Soomro et al [34]	-	0.739	0.956	0.948	0.844	-	0.748	0.962	0.947	0.855
Wang et al [50]	-	0.798	0.973	0.951	0.974	-	0.791	0.972	0.953	0.970
Proposed Method	980ms	0.802	0.974	0.959	0.948	944ms	0.801	0.969	0.961	0.945

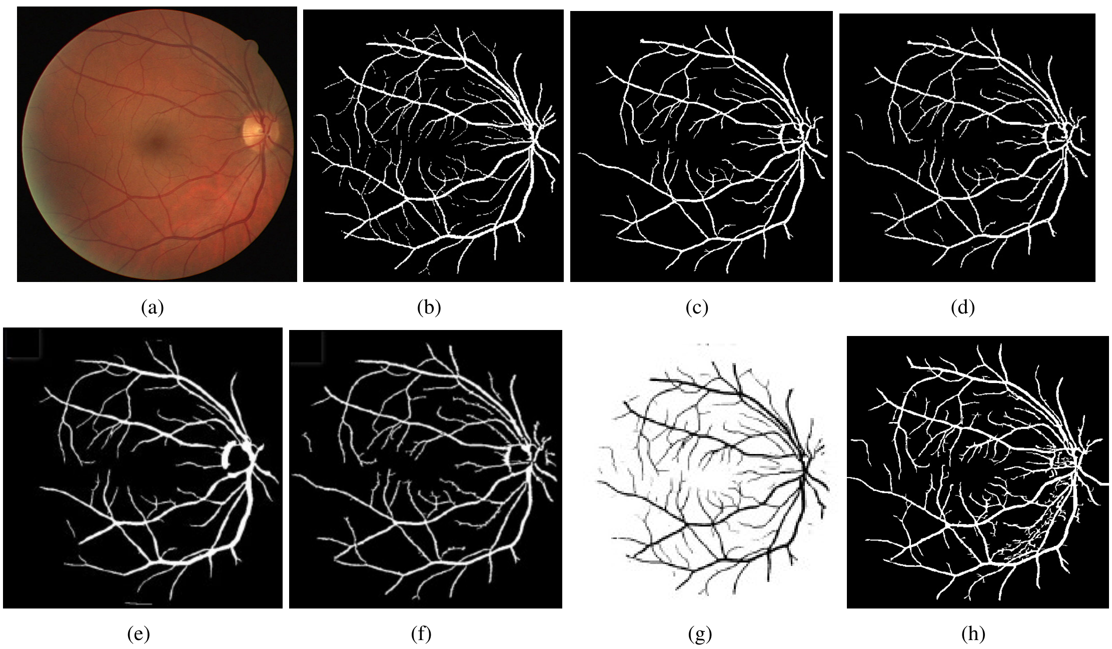


FIGURE 12. Analysis of tiny vessels detection image of different methods with our proposed output image. Figure (a) is an original retinal image, Figure (b) is a manual segmented image. Figure (c) represents output image of Nuygen's method, Figure (d) shows output image of Hou's method. Figure (e) and Figure (f) represents output images of Zhao's based on different filtering techniques. Figure (g) shows output image of Yan's method, and Figure (h) shows output image of proposed method.

compared to the other methods and a comparative sensitivity against Thangaraj *et al.* [51]. This obtained performance of the proposed method shows that our method can segment accurate retinal blood vessels. Our method is more robust in terms of execution time and few researchers have indicated the execution time shown in Table 5, and our method runs

TABLE 5. Comparison of proposed method with existing methods.

Database	DRIVE					STARE				
Methods	$Time$	Se	Sp	AC	AUC	$Time$	Se	Sp	AC	AUC
Staal et al[9]	-	-	-	0.946	-	-	-	-	0.951	-
Soares et al[10]	-	-	-	0.946	-	-	-	-	0.948	-
Mendonca et al[20]	-	0.734	0.976	0.945	0.855	-	0.699	0.973	0.944	0.836
Martinez-Perez et al[52]	-	0.724	0.965	0.934	0.845	-	0.750	0.956	0.941	0.853
Al-Diri et al[53]	-	0.728	0.955	-	0.842	-	0.752	0.968	-	0.860
Lupas et al[12]	-	0.720	-	0.959	-	-	-	-	-	-
Palomera-Perez et al[54]	-	0.66	0.961	0.922	0.811	-	0.779	0.940	0.924	0.860
Xinge et al[55]	-	0.741	0.975	0.943	0.858	-	0.726	0.975	0.949	0.851
Marin et al[56]	85ms	0.706	0.980	0.945	0.843	-	0.694	0.981	0.952	0.838
Fraz et al[11]	100s	0.741	0.981	0.948	0.974	-	0.754	0.973	0.953	0.977
Nguyen et al[57]	-	-	-	0.940	-	-	-	-	0.932	-
Hou et al[58]	-	0.735	0.969	0.941	0.961	-	0.734	0.965	0.933	0.957
Orlando et al[59]	1s	0.785	0.967	-	-	2.7s	-	-	0.951	-
Yin et al[60]	-	-	-	0.947	-	-	-	-	-	-
Roychowdhury et al[61]	3.115s	0.725	0.983	0.952	0.962	11.71s	0.772	0.973	0.951	0.969
Melinscak et al[62]	-	-	-	0.946	0.974	-	-	-	-	-
Annunziata et al[63]	-	-	-	-	-	-	0.713	0.984	0.956	0.965
Li et al[64]	70s	0.756	0.981	0.952	0.974	70s	0.773	0.984	0.962	0.987
Zhao et al[65]	-	0.716	0.978	0.944	0.848	-	0.776	0.954	0.943	0.865
Soomro et al[66]	-	0.713	0.968	0.941	0.841	-	0.711	0.965	0.942	0.838
Khan et al[67]	-	0.734	0.967	0.951	0.850	-	0.736	0.971	0.95	0.853
Zhang et al[68]	-	0.743	0.976	0.947	0.952	-	0.767	0.976	0.954	0.961
Orlando et al[69]	-	0.789	0.968	-	-	-	0.768	0.973	-	-
Ngo et al[70]	-	0.746	0.984	0.953	0.975	-	-	-	-	-
Guo et al [71]	-	-	-	-	0.947	-	-	-	-	0.946
Thangaraj et al [51]	-	0.801	0.975	0.961	0.888	-	0.834	0.953	0.944	0.894
Biswal et al[72]	-	0.71	0.97	0.95	-	-	0.70	0.97	0.95	-
Soomro et al[73]	-	0.752	0.976	0.953	-	-	0.786	0.982	0.967	-
Soomro et al[74]	-	0.745	0.962	0.948	-	-	0.784	0.976	0.951	-
Proposed Method	980ms	0.802	0.974	0.959	0.948	944ms	0.801	0.969	0.961	0.945

in less time to give a segmented image compared to others reported runtime methods.

There are two limitations observed visually in existing methods. First, the tiny vessels are missed and, secondly, the sensitivity is reduced due to the lack of detecting tiny vessels. These two problems can be solved by the segmentation of tiny vessels, which helps to improve the sensitivity. We compared the performance of our proposed method with the methods described for detecting tiny vessels such as Nguyen *et al.* [57], Hou [58], Zhao *et al.* [65] and Yan *et al.* [49]. It can clearly be seen that the proposed method gave more tiny vessels than those shown in Figure 12.

The capacity of the proposed method can be observed by the segmentation of vessels in their precise formats such as veins and arteries. Because the main problems that have not yet been addressed by many researchers are the segmentation of vessels in the presence of the centre of light reflex because it becomes difficult to specify the segmentation and identify the veins and arteries or identify the proper vessels. In parallel to the performance comparison, we conducted

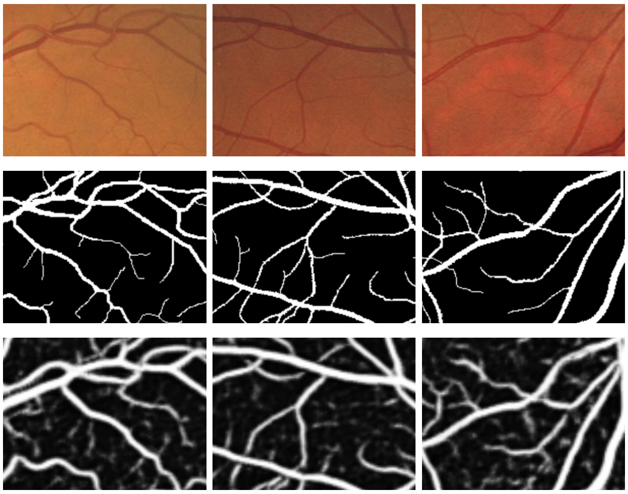


FIGURE 13. Illustration Retinal vessels (veins and arteries) network complexity analysis. Row 1 shows the retinal images patches affected with central light reflex, low-varying contrast and presence of abnormalities. Row 3 shows manual segmentation of each retinal image patches. Row 4 shows the segmented vessels of retinal image patches.

a thorough study to observe the vessels in different cases such as the centre of light reflex, the varying and low contrast. Figure 13 shows the segmented image areas of our proposed method in these cases and it is clearly observed that all vessels are correctly segmented according to their landmark image or ground truth image.

VI. CONCLUSION

The segmentation of retinal blood vessels based on CNN has generated great interest for many researchers over the last 5 years. Many models were proposed to solve this task but they failed to solve some problems regarding the retinal fundus image, especially the detection of tiny vessels. Precise vessel detection has played an important role in helping the ophthalmologist to analyze the progress of a disease and recommend timely treatment. In this research, we proposed pre-processing steps based on FCM to enhance the training images for the CNN model for accurate vessel detection. The proposed method was evaluated on the DRIVE and STARE databases and the reported performance was better or comparable to other existing methods, based on conventional image processing tactics or CNN-based methods.

There is still room for improvement for future work. We will study different CNN models, including residual convolutional blocks and simpler models to analyse the most important layer that will play an important role in improving performance. A second future direction is related to the available databases and we will work on generating synthetic images to enrich the training datasets to improve performance. Another research focus would be on the training process. We will train our CNN model using different loss functions to observe which loss function works much better on the image of the retinal vessels. These research points can, therefore, lead to the development of a more accurate and efficient model that can potentially be used in real scenarios.

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