An Enhanced Retinal Vessel Segmentation using Deep Convolution Neural Network

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Abstract. Accurate vessel segmentation in retinal images plays a vital role for retinopathy diagnosis and analysis. The presence of very thin vessels in low image contrast, on the other hand makes the segmentation task difficult. In the proposed method retinal vessels are segmented using multiscale Fully Convolved Convolutional Neural Network (FCCNN) architecture. The proposed architecture is trained for pixel classification to cope with the varying width and direction of the vessel structure in the retina. Green channel extraction gives better contrast difference between vessels and background. The skeletonization process is done which prevents the change in structure, thus the vasculature remains unchanged. In addition, an improved class balanced cross entropy loss function is included to avoid misclassification and imbalance problem. The proposed method is verified on public retinal vessel segmentation database (DRIVE). The accuracy of DRIVE FCCNN after 90 epochs was attained as 92.73% and the loss was attained as 0.0632. The experimental results show that segmentation results and accuracy obtained for FCNN are greater compared to the other architecture.

1. Introduction

Because of vascular occlusion, the most sensitive part of optic nerve of the eye is a delicate layer which strains on the rear part. Vascular occlusion, which results in blindness, is caused by ophthalmologic disorders such as diabetes retinopathy, high blood pressure, and arteriosclerosis. Blindness occurs due to the ophthalmologic diseases, which is caused by branching pattern morphological changes and vascular diameter. Many individuals are blinded as a result of retinal diseases all over the world due to the ultra-structural change in the blood vessels of retina. The analysis of retinal diseases requires the retinal vessels segmentation. As a result, precise segmentation of retinal vessel is becoming necessity for the proper treatment and diagnosis of retinal disorders. Ophthalmologic illnesses are diagnosed using retinal images, which includes the color fundus of 2-D and 3-D images. The retinal vessel is manually sectioned from fundus images by experts or professionals. This results in time ingesting and vessel segmentation that isn't acceptable. As a result, an automated segmentation of retinal vessels for dependable and strong segmentation may be needed.

2. Related Works

With the advancement of computer-assisted systems, various strategies for segmenting retinal blood vessels have been suggested. Both controlled and unsupervised segmentation are possible. In [4], Diego Marin suggested a technique that involves extracting functions for each pixel, including grey stage and momentum capabilities, and then applying those capabilities to the neural population for
classification. Since even the tiniest thinnest vessel will contribute to the green study, the analysis of retinal related illnesses necessitates extremely high precision in vessel extraction. The retinal vessel is manually sectioned from fundus images by experts or professionals. This results in time ingesting and vessel segmentation that isn't acceptable. As a result, automated retinal vessel segmentation is necessary for dependable and durable segmentation.

Function extraction and classification are part of the traditional supervised method. Feature extraction of vessel segmentation in retina is a simple task and at the same time, choosing the best function is necessary part for this. The selection of features must be distinct in order to properly section vessels. For retinal blood vessels segmentation, many researchers proposed and works with convolution neural network for better segmentation. Acting convolution, batch normalisation, and pooling operations are used by the convolutional neural group to extract first-rate feature. In [12], the author implemented the vessel tracking as the most commonly used method of blood vessel segmentation in retina. In [16], neighborhood’s developing process is introduced, in which the task is completed using morphological operations, matched straight out responses, and a complicated non-stop wavelet transform. In [14], CNN is used as a patch segmentation of retinal vessels which necessitates further reminiscence and is a lengthy operation. In [7], the author suggested using neighbourhood normalisation to improve segmentation of retinal vessels by reducing luminous and evaluation variants in retinal images, as well as a CNN structure that takes arbitrary duration input to produce output with green channel extraction. In [13], the author segments the retinal blood vessels with the help of Alex net, pre-educated group for segmentation. In [15], it offers a clear evaluation of the vessel and history, the author selected an inexperienced channel. They developed a neural community structure with four convolutional layers and one entirely related layer. In [10], the author suggested a convolutional neural network structure that ignores the elegance stability problem. As a result, non-vascular areas are mistakenly segmented as arteries. In [2] the author suggested a multiscale convolutional neural network to generate an opportunity map for segmentation to analyse the group stability characteristics of entropy loss function for improving the overall performance.

3. Proposed Module
3.1 Structure
Retinal images taken by fundus photography are capable of capturing vessels of thickness in the range at 36 micrometer to 180 micrometer as well as differing foreground lighting of blood vessels. Blood vessel contrast varies with respect to vessel thickness and location. Because of these variations, blood vessels segmentation in retina is a difficult challenge. The Proposed technique focuses on multiscale CNN to diagnose the retinal disorders by its segmented image. The structure of proposed module is shown in the Figure.1
3.2 Preprocessing
The green channel of DRIVE dataset was used to fill the poor contrast difference between background and vessels. After that the image is then normalised to decrease the effect of illumination, then it is enhanced more by Contrast Limited Adaptive Histogram Equalization (CLAHE) for further improvement.

3.3 Extraction
Clear distinction of the background & vessels can be obtained from the green channel (G-Channel). The saturated red channel (R-Channel) lacks the clarity. The darkest image of blue channel (B-Channel) lacks the precise details of the image. As a result, the extraction of red and blue channel misses the fine information of the image and the green channel provides much clarity to obtain greater differentiation between the background and vessels for the precise segmentation of the proposed module. Extracting the green channel image is illustrated as follows in the Figure. 2.

3.4 Skeletonization
Thin vessels are misplaced due to the difference in thickness between thick and skinny vessels, with thick vessels accounting for 77% of the total and thin vessels accounting for 23%. To compensate for the thickness discrepancy, all vessels inside the groundtruth are reduced to the same thickness, i.e. one pixel. Since groundtruth has been skeletonized, the group will analyse all roles in the same way. The skeletonization algorithm uses a thinning algorithm to remove the centre line pixel. The boundary points are thinned in two stages using the thinning algorithm. The two steps are repeated until the
image is free of pixels. The skeletonization mechanism prevents the structure from changing form, so the vasculature stays the same which is shown in the figure 3.

![Figure 3. Skelentonized Groundtruth Image](image)

### 3.5 Proposed Technique of CNN

Fully Convolved Convolutional Neural Network- FCCNN proposed Architecture is illustrated in the figure 4. The proposed system includes five encoder and decoder stages. Convolution layer is present in all stages of the encoder, the batch normalization and the rectification of linear unit is accompanied with all stages of convolution layer. A batch normalisation layer is used to speed up training, and the triggering process is a rectified linear unit. Each encoder's hidden stage performance is unpool and convolved twice. From the encoder level, the unpooling layer's pooling indices are extracted. The unpooling process is performed on the decoder stage using those indices. Throughout the point, each layer has the same number of filters. Softmax and the pixel classification layer make up the final layer. Every category of an image is assigned with probability value by the softmax layer. The classification of pixel layer categorises the image into non-vessel and vessel areas.

There are a total of 73 layers in the proposed architecture, including a batch normalisation and activation feature layer. At different levels of features, each layer provides valuable information for segmentation. The final convolution is a 1x1 convolution, which maps the channel to the same number of channels as the input. The final CNN classifier uses middle layer convolution features to learn richer multiscale information, allowing vessel edges to be precisely located and more tiny vessels to be detected. By combining the features in each plate, the identification precision of tiny thin vessels and vessel edges was greatly improved.
3.6 Class Weight

Pixelization of vessel and non vessel count was highly imbalanced for proper classification. i.e., In an fundus image, the labelled vessels in an image was just 10 percent and the remaining part pixels are non vessels, resulting the ruling class. Class weighting helps for aligning the classes and maintain accurate and stable distinction. Softmax and pixel classification layer are in responsible for pixel classification in the final category of layers. By integrating these two layers, the pixel image is predicted. The class weight is revised in the pixel classification layer. Class weighting provides robust segmentation to balance its category.

4. Experimentation

4.1 Database

The testing was performed in the Digital Retinal Image Vessel Extraction (DRIVE) database for segmenting the vessels. The drive totally contains 40 files. For training, we used 20 and for testing, remaining 20 was used. The ground truth of the image is segmented manually and get from the experts. The images in test dataset having 2 ground truths which comprises of standard and gold standard.

4.2 Evaluation Metrics

The accuracy of the result is evaluated using evaluation metrics. Confusion Matrix provides the true positive and true negative & also provides false positive and false negative are the four possible binary segmentation outcomes. The vessels are correctly predicted as vessels means true positive, or else it is false Negative, i.e., Incorrectly predicted. Similarly the non-vessels are correctly predicted as non-vessels means true negative, or else it is false positive. i.e., Incorrectly Predicted. Sensitivity, specificity and accuracy were the measures for finding the efficiency accuracy. Following formulae are used to measure Se, Sp, and Acc.
5. RESULT
5.1 Module 1
The extraction of green channel images are used as input to the proposed FCCNN architecture in module 1. The pixel mark data store is generated by marking the database's groundtruth as 255 for vessels and 0 for non-vessels. The fundus images' features and their corresponding groundtruth are learned by the network. The classification of pixels are used to segment the findings into non-vessel and vessel areas. The occurrence of vessel pixel counts is lower than that of non-vessel pixel counts. To match the pixel count of vessels, it was proposed to use the loss function. To prevent vessels from being misclassified as non-vessels. The pixel count of the vessel before class weight updating was found to be 10% of the image's total pixel count. As a result, boats were misclassified as non-vessels. The pixel count of vessels in the resized picture is 137752, while the pixel count of non-vessels is 2290195. Using the cross entropy loss feature, the modified class weightages of vessels and non-vessels are 17.6255 and 1.0601, respectively, meaning that vessel is given more weightage for robust vessel segmentation. The segmented result reveals that both thick and thin vessels are indistinguishable, as well as a lack of fine vessel is depicted in the figure 5.

\[ Se = \frac{TP}{TP+FN} \]  \hspace{1cm} (1)
\[ Sp = \frac{TN}{TN+FP} \]  \hspace{1cm} (2)
\[ Acc = \frac{TP+TN}{TP+TN+FN+FP} \]  \hspace{1cm} (3)

Figure 5. Segmented result of DRIVE Database using FCCNN for Module 1
a) Sample DRIVE image (b) Extraction of green channel (c) Groundtruth (d) Segmented result

5.2 Module 2
The extraction of green channel from DRIVE database is used as input to the proposed FCCNN architecture in module 2. The pixel mark data store is generated by labelling the database-provided skeletonised groundtruth as 255 for vessel and 0 for non-vessel. The network learns the features of the fundus images by skeletonizing their corresponding groundtruth. Due to the skeletonization of groundtruth, all dense and fine vessels are assigned equal weight. Figure 6 depicts the segmented result obtained for module 2.
5.3 Combining of Module 1 and Module 2
The key vessel thicknesses are found in the segmented module 1 result, but thin vessels are lost. Module 2 has well-segmented fine and main vessels, all of which are of uniform thickness. Both modules are combined to obtain the vessels of their respective thickness, i.e. image addition of module 1 and module 2 is performed, and the results are shown in figure 8. The fine vessels are well obtained by combining the segmented results of both modules, and the thickness of the main vessels is also preserved, as shown in figure 7.

5.4 Accuracy
DRIVE FCCNN has a higher sensitivity and specificity than other architectures. As compared to other architectures, the completely concatenated CNN achieves high accuracy. After 90 epochs, the precision of DRIVE FCCNN was 92.73 percent, and the loss was 0.06, as shown in Figure 8.
6. Conclusion
This paper proposes an automated retinal blood vessel segmentation using a multiscale completely convolved convolution neural network. The input image is resized in the proposed work, resulting in the loss of a small vessel. The extraction of green imagery channel makes the clear distinction between the background and the vessels more apparent. To solve this thickness discrepancy, all of the vessels in the ground truth are reduced to the same thickness. The skeletonization mechanism prevents the structure from changing form, so the vasculature stays the same. The key vessel thicknesses are obtained from the segmented product of module 1, but thin vessels are lost. Module 2 has well-segmented fine and main vessels that are all of the same thickness. Both modules are combined in order to acquire vessels of the required thickness. An enhanced cross entropy loss functions and batch normalization with FCCNN helps to improve the more robust segmentation of blood vessels. Experimental results indicate that the completely convolved CNN achieves better segmentation and accuracy than other proposed architectures. Retaining more vessels in retinal images is efficient. After 90 epochs, the accuracy of DRIVE FCCNN was found to be 92.73 percent, with a loss of 0.0632.

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