Retinal Blood Vessel Segmentation using Convolutional Neural Networks

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Abstract: Human beings often become victims to numerous diseases. Among these, diabetes stands out for its impairment of quality of life and even potential mortality. The diabetes needs to be properly taken care of, otherwise failure to detect its presence within proper time duration leads to a loss of life. According to the World Health Organization, the worldwide number of diabetic patients were 463 million during 2019 and is expected to cross 700 million by the 2045[i]. In the past, a lot of research has been carried out for retinal blood vessel segmentation for identification of Diabetic Retinopathy using various machine learning and deep learning models. In this research work, Convolutional Neural Network (CNN) and CLAHE are applied to tackle the problem of retinal blood vessel segmentation. Experimental evaluation shows that the proposed method outperforms with 0.9806 accuracy, quite competitive with respect to the state-of-art.

1 INTRODUCTION

Over the time, as age passes by, the human beings are entangled in the clutches of some familiar or unknown diseases. A major part of treatment for any disease involves an identification and detection of that disease. Although there are many techniques that are responsible for the disease detection, however, in most of the cases by the time the disease is detected, it is already at an acute stage, and ultimately it becomes un-curable, leading to the adverse circumstances. On the other hand, there are diseases like Diabetes where the mentioned tests are not so effective to diagnose its presence at an earlier stage.

As is stated by (Fong et al., 2004) the Diabetes is one of the prime reasons for blindness among the age group of 20-74 years. This means that the human retinas become blotted to such an extent, so that the person's vision goes down. During diabetes, the blood sugar level increases in the body to a very high level. Over a period of time can damage the retinal blood vessels and make them swell up. In some cases, the change is even visible to the naked eye. Also, possibility arises that it can block the blood from passing through the retinas, thus making the person blind. There are Type-1 and Type-2 kinds of diabetic patients. In the Type-1, initially destroys beta cells from the human body which causes in the stoppage of the insulin production. In the Type-2, the human body still produces insulin but it is unable to use it effectively. There are Type-1 (3.6%) patients, and Type-2 (1.6%) patients that are even blind (Dabelea et al., 2014) by blotting the retinal blood vessels. The retinal layer contains many nerves or photo-receptors that respond to light, thus enabling the person to see. These photo-receptors transmit optic nerve sensors and are converted into visual images. Most people do not care about eye conditions until it becomes too bad to the extent that the person becomes blind. Retinal disease is a visual disorder which ultimately even leads to blurriness in the eyes. Researchers (Bell et al. 2014) have stated that 280 million people in the world live with the visual impairments, 34 million among them are blind and 246 million with low vision. In

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2019, the number of diabetic patients touches 463 million, and is expected to cross 700 million by the 2045[i]. The visual impairment can be prevented with the early detection of the retinal detachment.

To work in this direction, here Convolutional Neural Network (CNN) and CLAHE are applied to dive into the retinal blood vessel segmentation. The proposed method outperforms with 0.9806 accuracy which is quite competitive with respect to the state-of-art works. Thus, the research contributions are stated here.

RC1: The optimized CLAHE + CNN model is trained and tested on the publically available DRIVE dataset and compared the result with state-of art.

RC2: Performance evaluation is better than other approaches over the DRIVE dataset.

Rest of the paper is organized as follows. Section 2 talks about related work, Section 3 discusses proposed work, Section 4 illustrates results & analysis, and Section 5 concludes the paper.

2 RELATED WORK

Researchers (Chaudhuri et al., 1989) have used two dimensional filters to analyze the blood vessel segmentation. A feature-removal operator based on visual and real-estate properties is notified. The gray cross section of artery is measured by Gaussian curve. The signal acquisition determines the successive sequence of blood vessels in the images. There are 12 varied templates that are created to search for ship-parts in the available directions.

(Marın et al., 2010) have introduced approach for finding blood vessels in the digital images of eyes. Their method uses Neural Network (NN) and incorporates 7-D vector with grey and secondary features that are built into the pixel system representation. It is tested on the publicly available datasets- DRIVE and STARE. These datasets are commonly used because they contain images of the retina where the structure of blood vessels is accurately marked by experts.

(Fraz et al., 2012) have learnt the blood vessel segmentation problem using a hybrid method which uses the concept of acquisition of vessel centerline for the first order from the Gaussian. Also, observed retrieval vessels while connecting the center lines with a map of the position itself. They are able to get 97% accuracy. This paper reports the default way to separate blood vessels in the images above. A unique combination of ship acquisition techniques and slow-flight aircraft are introduced to remove the artery tree from the images. Mathematics of morphology is already a good way to measure blood vessels in the retina.

(Odstrcilik et al., 2013) have identified the development of a two-way filter that is consistent with Gaussian's role as a character. They have explored the path to STARE, DRIVE and HRF's decision-making process. They have designed five 2-D filters according to standard container category profiles and watched five shipwrecks from the thinnest to the too big. Each image is processed to match one in the five characters. Because the same filters in each image, the process is slower. The method effectiveness lies upon how accurate team of ships is divided into the five parts.

(Sreejini and Govindan, 2015) have applied improvised multi-scale matched filter for the blood vessel segmentation using Particle Swarm Optimization (PSO) (Jain et al., 2021). The same filtering concept is widely used in the area of retinal detachment. Multi-scale standard filters have higher performance than the single-scale filters. The method uses advanced audio compression features of international filters.

(Singh and Srivastava, 2016) have utilized second hand derivative of Gaussian as a filter for retinal blood vessels segmentation. The method corresponding to the measured filter are simple and effective. However, the corresponding filter test detects both vessels and non-vessel terminals which gives false ships i.e., non-ship acquisitions. To overcome the problem of finding non-ship edges, an extension of the matching filter based on the Second Gaussian discovery (SDOG-MF) is considered useful for the separation of small and narrow retinal blood vessels.

(Yao et al., 2016) have discussed CNN based algorithm. Each pixel and its image neighbors are tested by the CNN. The effects of the first classification of fundus images are refined by two phases of binarization and morphological performance respectively. The algorithm is tested over the DRIVE database. The data sensitivity is 0.7731, which is very close to that of the text annotation.

(Sun et al., 2017) have illustrated four CNN architectures (AlexNet, GoogLeNet, VGG-16, and ResNet-50) from ImageNet image classification task to Retinal fundus images quality classification. The top two networks are picked out and then jointly fine-tune them. The accuracy for different methods are found to be as AlexNet (96.53%), GoogLeNet (97.04%), VGG-16 (96.87%), ResNet-50 (96.20%), Joint CNN with GoogLeNet (97.00%), and Joint CNN with VGG-16 (97.12%) repectively.

(Jebaseeli et al., 2019) have pre-processed retinal blood vessels dataset through CLAHE- Contrast Limited Adaptive Histogram Equalization, feature vectors through TPCNN- Tandem Pulse Coupled Neural Network, classification and extraction through DLBSVM- Deep Learning Based Support Vector Machine. It gives improved segmentation results of sensitivity, specificity and accuracy as 0.7445, 0.9940, and 0.9897 accuracy respectively. However, certain issues are quite unclear such as how deep learning learns, whether neural net relays upon certain images with the datasets, are they non-transferable to all retinal photography. These are limitations of accuracy for the stated technique.

(Wang et al., 2019) have illustrated novel separation framework and a strong cascade separation of the retinal vessel. Unlike other non-linear partitions that require a pre-defined non-linear kernel or repeated training, a separate cascade editing framework is trained through the process of a single pass transfer. Therefore, degree of non-compliance with the separate line is not defined in advance, but is determined by the complexity of data structures.

(Saroj et al., 2020) have worked upon a matched filter approach with kernel as a Fréchet probability distribution function. It uses principal component analysis for the color conversion and CLAHE during pre-processing. While during post-processing, it uses entropy based optimal thresholding, and filtering by the length. The specificity, sensitivity and accuracy for the STARE- 0.9724, 0.7278, 0.9509 and for the DRIVE- 0.9761, 0.7307, 0.9544 respectively.

(Escorcia-Gutierrez et al., 2021) have worked upon Portfolio Theory of Markowitz for diabetic retinopathy via optic disc. It produces an innovative color fusion model which is applied over DRIVE, Messidor, HRF, and in–house dataset (Hospital Universitari Sant Joan de Reus, Spain). It gives an accuracy and overlap as 0.9 and 0.80 respectively with minimal execution time of 0.05seconds.

(Gegundez-Arias et al., 2021) have presented a robust CNN based on UNet vessel segmentation method in fundus images. It combines residual blocks and batch normalization in the up-down scaling. From actual images, patches are extracted and trained with loss function while looking at every pixel distance towards vascular tree, while output produces binarized probability map of pixels. The method is experimented over DRIVE, STARE and CHASE_Db1.

(Pal et al., 2021) have proposed the Twin network retinal scan system which extracts feature maps of both query and database samples from the deep CNN. The approach exploits deep features without the resource, space and computation exhaustive network training phase. The different variations of retrieval performances are evaluated- AMD-Normal, DME-Normal, AMD-DME, AMD-DME-Normal. The system retrieves similar scans from a dataset of abnormal and normal retinal scans with precision (0.7571).

(Rajagopalan et al., 2021) have worked upon the CNN model for the detection of retinal disorders. The model classifies three types of retinal disorders- Choroidal neovascularization (CNV), Drusen macular degeneration (DMD) and Diabetic macular edema (DME). It provides an accuracy (0.9701), sensitivity (0.9343), and specificity (0.9807) respectively.

3 PROPOSED WORK

The architecture of the proposed Retinal Blood Vessel Segmentation method is described in Figure 1.

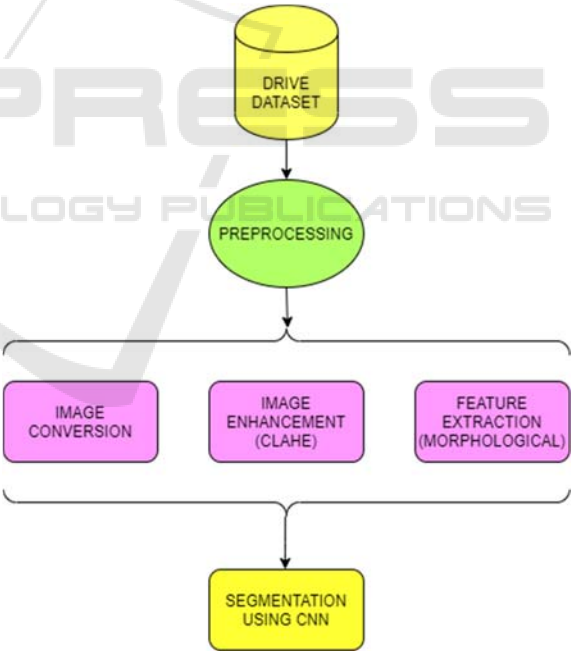


Figure 1: Basic architecture of proposed work.

The DRIVE dataset is fed into the system which undergoes Pre-processing, namely- Image Conversion, Image Enhancement (CLAHE) and feature extraction (morphological). The image conversion, converts the dataset images from colour to grey format, applies the equalizer CLAHE for converting the image to contrast form i.e.

Enhancement. The feature extraction phase undergoes morphological feature, which is followed by Segmentation using Convolutional Neural Networks.

3.1 Dataset Discussion

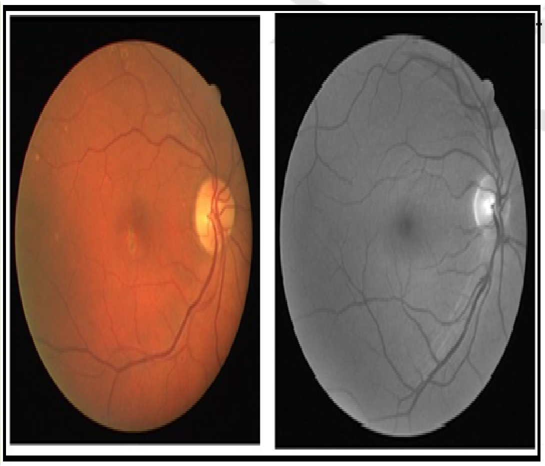
The proposed Retinal Blood Vessel Segmentation model is executed over the chosen DRIVE dataset (Staal et al., 2004). The DRIVE dataset contains data from the diabetic program of Netherlands which is collected from 400 people within age of 25-90 years. This wide age group is considered to avoid model overfitting and is a potential age range for the diabetic patients. This dataset is also considered by several researchers (Yao et al., 2016; Albargathe et al., 2021; Escorcia-Gutierrez et al., 2021) and comprises of 20 training and 20 test images respectively.

3.2 Pre-processing

Once the DRIVE dataset is extracted, the system undergoes pre-processing phase as follows.

3.2.1 Colour to Grey Conversion

The grey scaling process converts an image from different colour spaces into the shades of grey, as is seen in Figure 2.



(a) Colored Image (b) Grey Scale Image

Figure 2: Color to grey scale conversion.

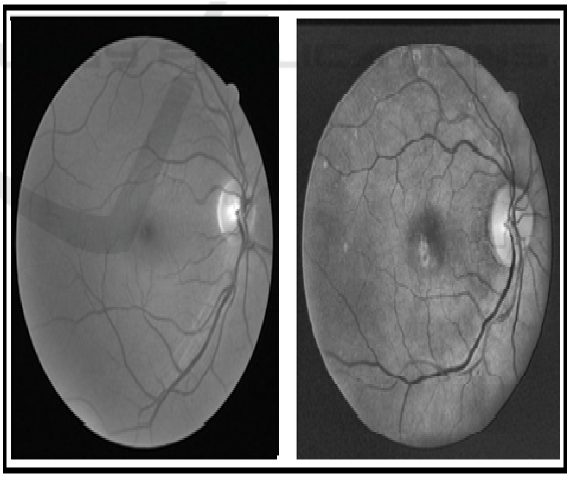
The coloured spaces are such as RGB, CMYK, and HSV etc. that are converted into the shades of grey- i.e., in between complete black and complete white. The python programming based OpenCV library is used to perform the grey scale conversion. The primary reason of doing this conversion is to provide accurate results and faster processing, as there are only two values- 0 and 1 in the resultant colour histogram.

3.2.2 Applying Clahe

CLAHE is an adjustable extension of Histogram Equalization which is followed by the threshold. It helps in preserving the local contrast characteristics of an image dynamically.

In the initial steps, stress is on the local contrast rather than global contrast of the image. The global histogram balance doesn't stress on local contrast enhancements, and subsequently have minor contrast differences which is extremely common in NPDR imagery and is totally missed if the quantity of pixels falling in a specific dark shade is too little. To take care of this issue, the proposed calculation is characterized to work adaptively on the image that is to be improved, not like normal standard histogram adjustment. It improves the contrast upgrade on local image data in a divide and overcome way, subsequently effectively handles the global distortion of the image.

All in all, the fundamental thought of the calculation is to separate the image into various little, non-covering context oriented areas which are called Tiles (Figure 3).



(a) Original Image (b) Enhanced Image

Figure 3: Image enhancement using CLAHE.

3.2.3 Feature Extraction

In the feature extraction phase, the morphological features of the images of an eye are fed into the machine learning model to obtain the relevant results. The encoder-decoder approach is used to convert an image data into embedding's which is fed into the Convolutional Neural Networks.

3.3 Segmentation

Identifying the sets of pixels which can go together is the problem of image segmentation. Pixel-level categorization is another name for this method. To put it in another way, it comprises dividing images into many segments or objects. One of the most important applications in the computer vision area is image segmentation (Moccia et al., 2018). It is used in a variety of fields, including medicine and intelligent transportation.

Image segmentation has advanced dramatically with the deep neural networks (Siddiqui et al., 2020). Among the deep learning concepts, CNN which is also known as CovNet is useful for image detection and recognition (Noh et al., 2019). The CNN inputs image data, passes it through different layers- convolutional, pooling, flattened and fully connected layers and classifies data into appropriate category.

3.3.1 Convolutional Layer

It takes input as an image, extracts features and preserves relationship among image pixels. It stores the feature of an image as different sizes of matrix then reduces the size of the matrix by taking filters of varied sizes. The obtained reduced matrix is called as Feature Map.

3.3.2 Non-Linear Activation Function

It uses non-linear activation function i.e., ReLU- Rectified Linear Unit, mathematical function which is given in equation (1).

$$f(x) = \max(0, x) \begin{cases} 1, \textit{positive} \quad \textit{output} \\ o, \textit{negative} \quad \textit{output} \end{cases} \tag{1}$$

3.3.3 Pooling Layer

It reduces the dimension of features map while retaining important features of the image. The pooling layers contains several variations like max pooling, average pooling, and min pooling. In this work, max pooling is used which contains maximum values of the feature maps.

3.3.4 Flattening Layer

It is used to flatten the pooled matrix to its corresponding vector which is serving as an input for fully connected layer.

3.3.5 Fully Connected Layer

It contains several layers with many nodes. It contains an input layer (first layer), output layer (last layer), and hidden layers (other layers). In the fully connection, each node is connected to every node of its next layer. In the last layer, sigmoid function categorizes the image to its most accurate category while within rest of the layers, ReLU function is applied.

4 RESULTS & ANALYSIS

The results of the proposed method are computed mainly in terms of the model accuracy.

4.1 Model Accuracy

On training over the DRIVE dataset, using encoder-decoder of CNN, the model gives an accuracy of 0.9806.

4.2 Training and Validation

The accuracy curve and loss curve are illustrated here.

4.2.1 Accuracy Curve

The training and validation accuracy curve of the method is described in Figure 4.

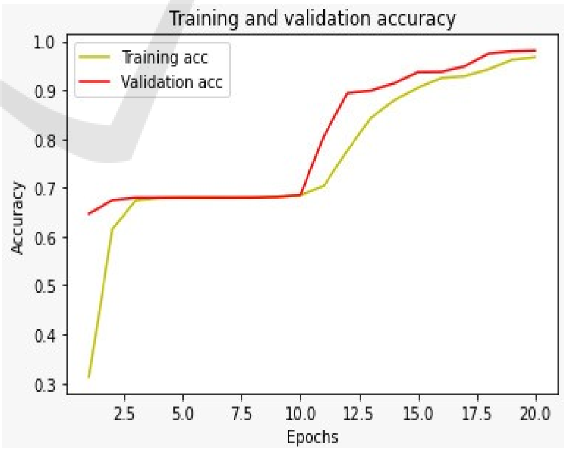


Figure 4: Training and validation accuracy curve.

4.2.2 Loss Curve

The training and validation loss curve of the proposed method is described in Figure 5.

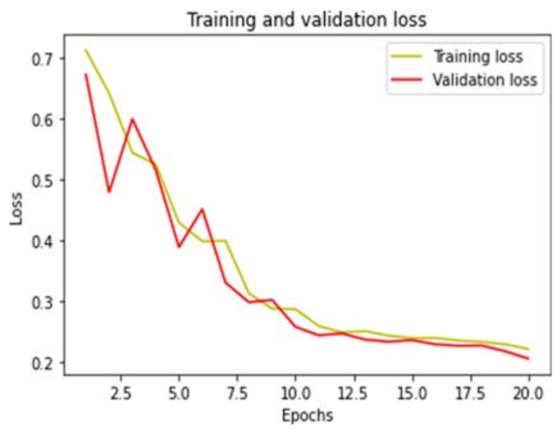


Figure 5: Training and validation loss curve.

4.3 State-of-Art Comparison

The proposed work is compared with respect to the state-of-art by the other researchers (Table 1).

Table 1: Comparative analysis over DRIVE dataset.

S.No.	References	Method	Accuracy
1	Marın et al., 2010	Neural Networks	0.9452
2	Fraz et al., 2012	Hybrid Approach	0.9430
3	Sreejini and Govindan, 2015	Multi-scale Matched Filter	0.9633
4	Singh and Srivastava, 2016	SDOG-MF	0.9645
5	Yao et al., 2016	CNN	0.9360
6	Soomro et al., 2018	Independent Component Analysis	0.9530
7	Soomro et al., 2019	FCM + CNN	0.9590
8	Wang et al., 2019	Cascade Classification	0.9541
9	Jebaseeli et al., 2019	Tandem Pulse CNN	0.9897
10	Saroj et al., 2020	Frechet PDF	0.9544
11	Albargathe et al., 2021	H-Minima	0.9672
12	Escorcia-Gutierrez et al., 2021	Markowitz	0.9556
13	Gegundez-Arias et al., 2021	Modified UNet	0.9547
14	**Proposed Work**	**CLAHE + CNN**	**0.9806**

5 CONCLUSIONS

In this work, CLAHE + CNN is applied for the retinal blood vessel segmentation of images over the DRIVE dataset. The method undergoes pre-processing- grey scale conversion and CLAHE, feature extraction using morphological feature, segmentation, training and prediction using CNN. The results are evaluated in terms of the model accuracy as 0.9806 which is quite competitive with respect to the state-of-art work over the DRIVE. Because of the ease-to-use and good performance, the proposed method accelerates the diagnosis of Diabetic Retinopathy. In future, model accuracy can be enhanced further using more deep learning strategies.

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END NOTES

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