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Segmentation and Detection of Abnormalities in Retinal Blood Vessels

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Abstract: Blood vessel extraction is a critical step in gaining access to various important features in the retinal images. This paper presents a fast and effective method of segmentation of the blood vessels. The ophthalmologists can diagnose the disorders of the eye using the technology of Digital Image Processing. The patients' retinal fundus images are procured by capturing the background of the eye using a digital fundus camera. Numerous methods of the segmentation of retinal blood vessels based on convolutionary neural networks have been proposed recently, and the U-net has been applied successfully in order to view segmentation as a new segmentation network. Retinal vessels are small and therefore the features of retinal vessels can be effectively learned through the technique of patch-based learning. The presence of retinopathy can further be recognized using the segmented images thus obtained. This Automated method of disease detection can be used instead of the manual method in order to save time. In this report, we have proposed a new paradigm for the retinal vessel segmentation based on the U-net and the classification of retinopathy based on the Convolutional Nueral Network.
Keywords: Blood Vessels, U-net, Convolutional Neural Network, Retinal Fundus images, Patch based Learning, Retinopathy

I. INTRODUCTION

Segmentation of the retinal blood vessels plays a vital role in the identification of any change that arise in the blood vessels and it also provides an understanding about the vessel position. The automatic retinal map generation is used to treat the age-linked macular degeneration. Retinal blood vessel segmentation is the fundamental function of retinal fundus image analysis since certain retinal blood vessel features, such as distance, tortuosity, and branching pattern are essential disease symptoms. The optic disk and the fovea present in the fundus image can be easily identified based on the position of the vessels. There are two main groups in the retinal vessel segmentation method which is categorized as supervised and unsupervised. The approaches in supervised learning gain knowledge from a model in order to decide whether a pixel is a vessel or not, with the manual label support. The manual methods are found to be expensive in comparison to the unsupervised methods due to the extraction of different types of features and training of complex classifiers with a vast amount of data.

Diabetic retinopathy (DR) is a disease where the blood sugar level is constantly very high and the fragile blood vessels lining the inside portion of the retina get impaired and start to leak, thereby distorting the vision. In the past two decades, about two thirds of the visual impairment and the increase in blindness is caused due to diabetes. Medical experts are currently evaluating the severity and degree of retinopathy associated with a person with diabetes by using the retinal images of the patient's eyes. The screening programs generate the retinal images and this keeps on increasing with the number of diabetes patients which ultimately results in a large labor-intensive burden on medical experts and also cost to healthcare services. With an automated system, this could be alleviated either as support for the work of medical experts, or as a complete tool for diagnostic purposes.

An imperative task in surgical planning and computer-aided diagnosis of diabetic retinopathy is the accurate retinal blood vessel segmentation. The assessment of the retinal blood vessel manually is not conceivable since the vascular width estimation is normally pivotal. The possible solution to this problem is the use of fundus images which are analyzed by the computer scheme followed by the retinal vessel segmentation procedure. The automatic disease monitoring system greatly decreases ophthalmologist load.

II. LITERATURE REVIEW

Many techniques for segmentation are published in the literature. They can be categorized into supervised and unsupervised methods. Supervised strategies call for initial knowledge on the retinal blood vessel segmentation. Achievements of the supervised techniques are much better than methods which are unsupervised. In this field, the related work is summarized as follows.

Toufique Ahmed Soomro *et al*. [1] proposed a new method to detect the blood vessels of the retina precisely using the CNN technique. First, a pre-processing method which was based on Fuzzy logic and image processing tactics was applied. In the second step, a fully strided encoder decoder CNN model was used to produce the segmented images. The network was then trained using the Dice Loss function that was used to solve the class imbalance problem present in the database. The last step was the removal of the shadow of the Optic disc and the pixels that were noisy which was achieved using post processing methods. Zhongming Luo *et al.* [2] proposed an algorithm for retinal vessel image segmentation based on improved U-Net network. The contrast between the background and the blood vessels was highlighted by the Fundus Image Enhancements which were conducted during pre-processing stages. The fundus images thus obtained were converted into gray scale images so as to balance the original image size and lessen the model intricacy. Sehrish Qummar *et al.* [3] used the Kaggle dataset of the retinal images available publicly to train and group the five Deep Convolutional Neural Network for the purpose of encoding the rich features and improve the classification for different Diabetic Retinopathy stages. Dhimas Arief Dharmawan *et al.* [4] pooled the pre-processing and the post-processing phases so as to achieve an absolute retinal vessel extraction scheme. The evaluation of the method was carried out using the DRIVE and STARE databases, equipped with ground truths. Mandalina Savu *et al.* [5] proposed convolutional neural network architecture for retinal blood vessel segmentation. The CNN was implemented using GPU programming in MATLAB which ensured high speed of processing. Duoduo Gou *et al.* [6] presented an effective retinal blood vessel extraction method to detect fine vessels more accurately for the diagnosis of eye diseases. This methodology detects many fine vessels drowned by noise and has good width estimation. A.Elbalaoui *et al.* [7] presented a novel method for the detection of retinal blood vessels in the fundus images. The performance was compared and analysed on DRIVE, STARE and CHASE-DB databases of retinal images by means of various measures including accuracy, sensitivity and specificity. Ambaji S Jadhav *et al.* [8] constructed an effective system which was used for the analysis of the key features of retinal images for diabetic retinopathy by using image processing techniques. The method used was applicable for both unhealthy and healthy images.

III. PROPOSED METHODOLOGY

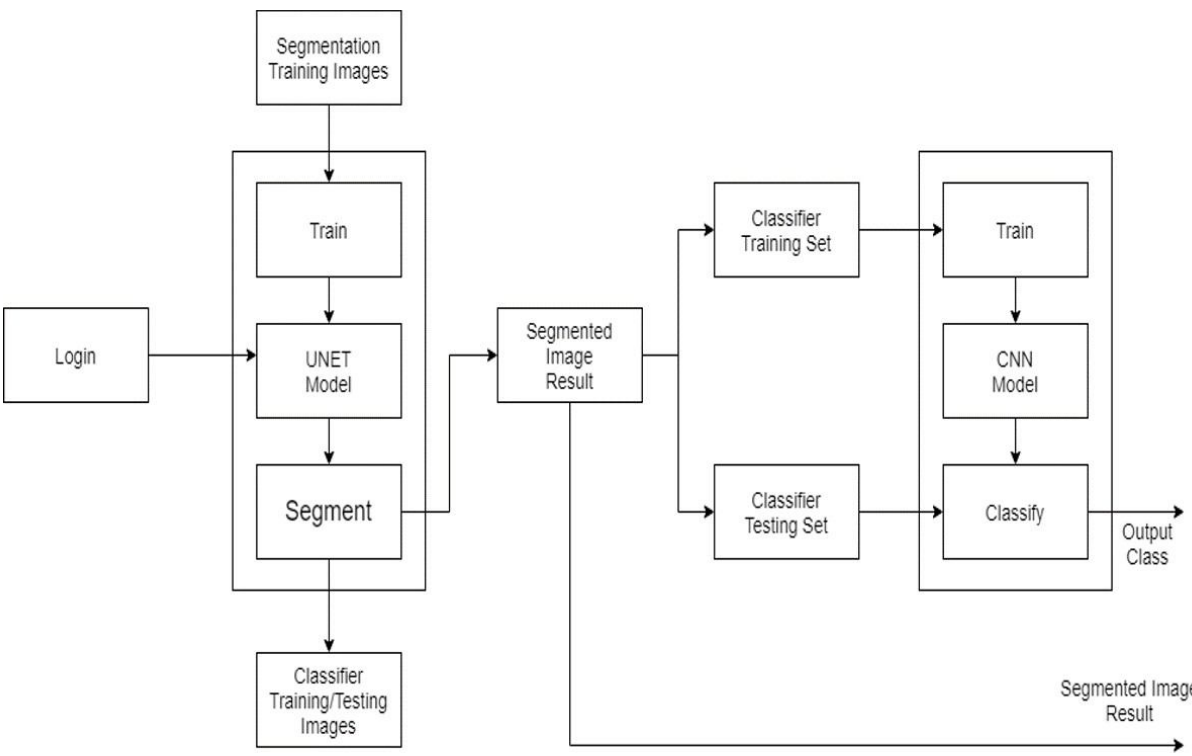

Fig. 1 Architecture of the Proposed System

The system comprises of three stages namely Login, Segmentation and Classification. The user is required to input all the required information in the first stage i.e., the Login. The segmentation process involves Pre-Processing, which outputs the G Channel images and these images are used for Patch Extraction. If the user requires classification of abnormalities, then these segments are given to the CNN which classifies the segments into class 0 (no retinopathy) and class 1 (retinopathy). The UNET model is trained further and segmentation is done. The classification process consists of loading the CNN Model, training it and classifying it.

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A. Data Acquisition

Many deep learning applications try to solve problems using the provided input data. So here we need a source to train and segment the images using the U-net and classify using CNN whether there is presence of abnormalities in the given dataset. We have used the DRIVE dataset in our project. The photographs for this database were taken from a screening program on Diabetic Retinopathy which had taken place in Netherlands. Forty photographs are selected randomly where 33 images don't show any hint of diabetic retinopathy and seven show sign of mild diabetic retinopathy. The images were compressed to JPEG format. The camera used to capture these images was Cannon CR5 non-mydriatic 3CCD. This dataset contains 40 images of retinal blood vessels from which 20 images are used for training and 20 are used for testing purpose.

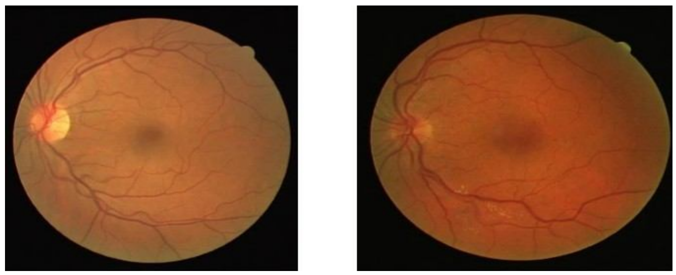

Fig. 2 Sample of the collected dataset

B. Data pre-processing

Data Pre-processing is a technique in which the raw data is transformed into a clean collection of data. The steps are as follows:

1) *Reshape of Images:* The input images must have the same size for any model in machine learning to operate. The dataset we are using contains images of different sizes and therefore we reshape them into a fixed size of 565x584 pixels.
2) *Selection of Retinal Channel*: Image Enhancement technique is used during the pre-processing of an image. The purpose of applying the pre-processing steps on the training data is to subdue the irregular illumination present within the images and to augment the low and varying contrasts. The crucial step is to pick the well contrasted RGB channel and therefore we make use of fuzzy C-Mean to get rid of the non-uniform illumination with a morphological operation and take away the noise. We made use of the colour fundus images of the retina for the segmentation purpose. They are monochrome and are collected from the fundus camera present in the hospitals. These images consist of 3 channels. They are red, green and blue. The red channel has luminance and noise. The blue channel contains noise and shade while the green channel consists of less noise and provides good observation compared to red and blue. The main aim is to process the images efficiently and construct the data suitable for training. The employment of the grayscale representation removes the descriptors rather than operating directly on the colour images. The gray-scale representation is most widely used due to its reduced computational requirements. Colour images process unnecessary information which will increase the processing data needed to realize the specified performance. Therefore, the conversion of the colour retinal fundus image into a gray scale format is very essential for further processing because of the manifestation of the blood vessels within the green channel with strong contrast to the red and blue channels. Thus, we selected the green channel for further processing and training.
3) *Train-Test Split:* At this stage, the dataset is split into two categories namely training and testing data. The training set consists of a total of 2,00,000 images as every image is divided into 10,000 parts. These 2,00,000 images thus obtained is used to train our model. The performance of the model is evaluated using the testing data which consists of 20 images. Since the model is evaluated using the data which is not familiar to it, the splitting of the dataset is very much essential. The U-net algorithm segments the images when the model is tested and if the user wishes to classify the segments further, then the segments is given as input to the CNN model which detects the presence of diabetic retinopathy.

C. Patch Extraction

The manual segmentation done on the fundus images was time consuming; prone to many errors and the ground truths of the retinal vessels was small. We have used Patch based learning technique in our methodology throughout. The Random Extraction Strategy is implemented which extracts the training and the labeled patches from the training and labeled images respectively. The model parameters are further trained using these patches. The extraction strategy is overlapped from the test images in order to extract the test patches. The expected outcome is then reconstructed by a sequential reconstruction strategy overlapping-patch. During the training phase, the patches are collected randomly from the training images and thus the number of patches for each image is equal.

Algorithm 1. Image patches random extraction strategy

Input: Source image, ground truth
Output: Patches_source and patches_ground

Calculate patches number ***N_patch_per_image*** for each image basing on the principle of equal distribution
for i=1 to *N_images*
k=0
while k< *N_patch_per_image*
generate the central coordinates of patch randomly
judge the central coordinates of image patch inside FOV
produce patches_source and patches_ground
k=k+1
return patches_source and patches_ground

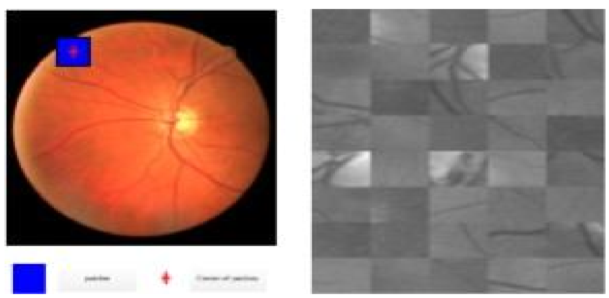

Fig. 3 Patch extraction

During the testing process, the overlapping extraction strategy is used in order to divide the images into patches. The number of patches to be obtained from each image is calculated using the following:

$$N\_patches\_per\_img = \left(\left\lfloor \frac{img\_h - patch\_h}{stride\_h} \right\rfloor + 1 \right) \times \left(\left\lfloor \frac{img\_w - patch\_w}{stride\_w} \right\rfloor + 1 \right)$$

The overlapping extraction strategy algorithm is given below.

Algorithm 2. Overlapping-patches sequential reconstruction strategy

Input: Patch-base prediction result *preds*, image size *img_h*, *img_w*, stride *stride_h*, *strid_w*
Output: Final segmentation result *final_avg*

Calculate patches number *N_patches_h* in height for each image
Calculate patches number in width *N_patches_w* for each image
Calculate patches number *N_patches_img* for each image
for i=1 to *N_patches_img*
for h=1 to *N_patches_h*
for w=1 to *N_patches_w*.
obtain pixel predicted probability *full_pro*
obtain pixel predicted frequency *full_sum*
Calculate final segmentation result *final_avg*
return final segmentation result

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In the algorithm 2, the number of images and also the height and width of the patched images is calculated using the equations given below:

$$N\_patches\_h = \left\lfloor \frac{img\_h - patch\_h}{stride\_h} \right\rfloor + 1$$

$$N\_patches\_w = \left\lfloor \frac{img\_w - patch\_w}{stride\_w} \right\rfloor + 1$$

$$N\_patches\_img = N\_patches\_h \times N\_patches\_w$$

D. U- net Architecture

The U-net model is loaded with the extracted patches which are used to segment the blood vessels.

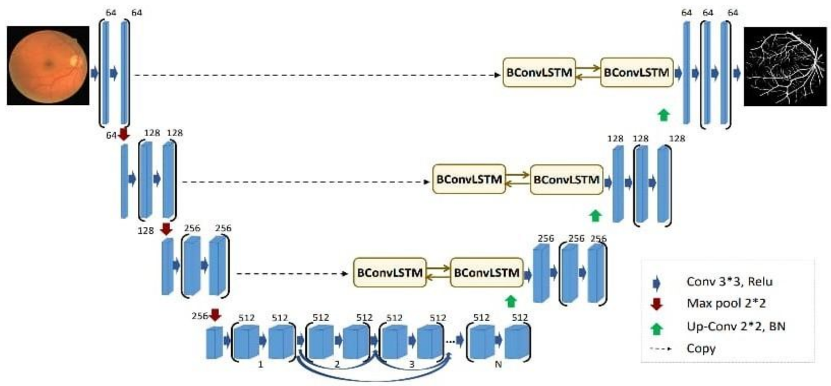

Fig. 4 BCD U-net with bi-directional ConvLSTM in the skip connections and densely connected convolution.

The U-net is a convolutionary network architecture used for quick and accurate image segmentation activities. We take complete advantage of U-net, bi-directional ConvLSTM for segmenting the retinal blood vessels.

The BCDU-net mentioned above is used as an extension of U-net, which yields better performance than the state-of-the-art alternatives for the task of segmentation. There are four steps in the architecture of the contracting path and each step comprises of two convolutionary 3 x 3 filters followed by a 2 x 2 maxpooling and the activation function used is ReLU. The feature maps are also doubled at each stage. Gradually, the contracting path contains the image representations that are extracted, which also results in the raise of layer-by-layer dimension of the representation.

E. CNN Architecture

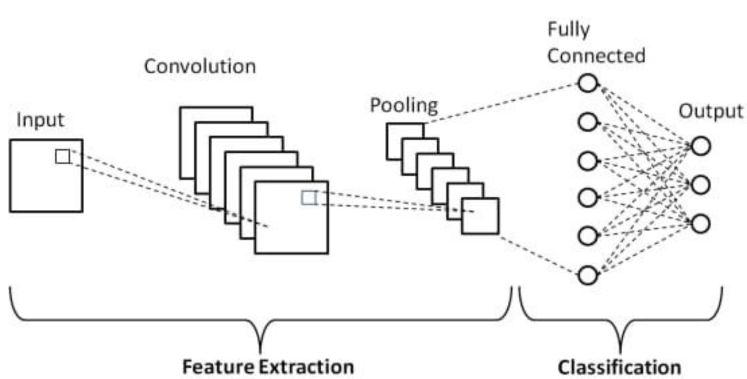

Fig. 5 CNN Architecture

Classification process consists of the pre processing of the stored segmented images which is followed by feature extraction. The extracted features thus obtained are used for the CNN model training. The CNN model acts as the classifier which classifies whether there is retinopathy or no retinopathy. CNN model also accurately classifies the severity. Unlike other machine learning algorithms, CNN learns by matching the parts of the image which helps it to tolerate the moved patterns, thicker and thinner, larger or smaller, and rotated as well.

The first filtered layer is Convolution which produces the complete map of the image which is basically the sum of the patterns that are matching. This is achieved based on the method of mathematical filtering. In this method, the images are mapped to a patch, multiplied by each pixel of the image, summing it up and then dividing it by the total pixels present in that particular region. The next filtered sheet, pooling, makes the location less responsive to the CNN. Pooling selects a window size, iterates through a moving range and then takes the maximum value in each window and thus shrinks the image stack. It is constructed by lessening each matrix selected in the previous stage. The final filtered layer, ReLU, is a process of computational units which are rarely used. ReLU involves a process called normalization. ReLU layers show similar results to the filtered layer described above with the exclusion of its lack of negative values. After processing all the layers, a completely connected layer decides the final output. After processing all the layers, a fully connected layer decides the final output. The highly filtered images are translated into votes by this layer.

In our designed system, we employ the Convolutional Nueral Network to categorize the blood vessel segments into class 0 (no retinopathy) and class 1 (retinopathy). We have used the Classroom Dataset to train our CNN Model. The model is trained by taking 1,000 images of each class i.e., class 0 (no retinopathy) and class 1 (retinopathy). Once the model is trained, it is saved and stored. When we test the model, the blood vessel segments are provided as input and the CNN model outputs the class.

IV. RESULTS AND DISCUSSIONS

The efficacy of the method proposed was demonstrated using the public DRIVE dataset. The DRIVE database is composed of sets of training and testing images. The training set includes source image, mask image and ground truth; 20 source images (RGB) with a resolution of 565 x 584 were displayed. The Classroom Dataset was used for the classification of the retinal blood vessel segments into class 0 and class 1. We used 1,000 images in each class i.e., with retinopathy and without retinopathy for the training purposes.

Green channel extraction is carried out before sending to the U-net model. The first image shown in figure 6 is after the green channel extraction is done and the second one is the segmented image obtained as output.

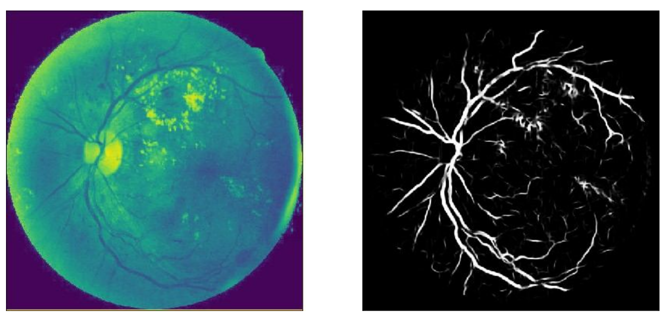

Fig. 6 Image obtained after Green Channel Extraction and the obtained output

The image shown in fig. 7 is the image of the retinal blood vessel belonging to class 0 and fig. 8 shows the segmented output.

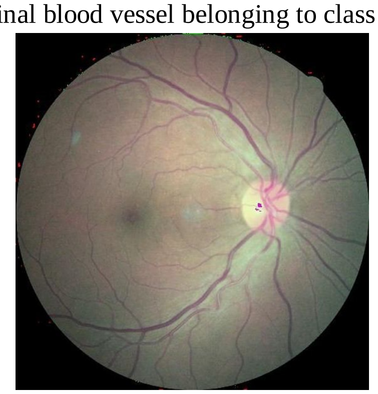

Fig. 7 Image of Retinal Blood Vessel in Class 0

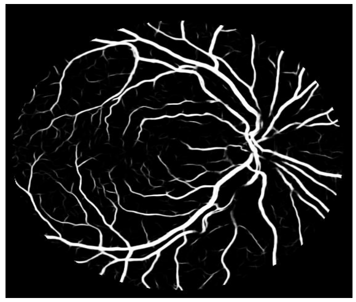

Fig. 8 Output of Retinal Blood Vessel in Class 0

The graph of Training & Validation Loss & Accuracy say that the validation loss increases and validation accuracy is 70%.

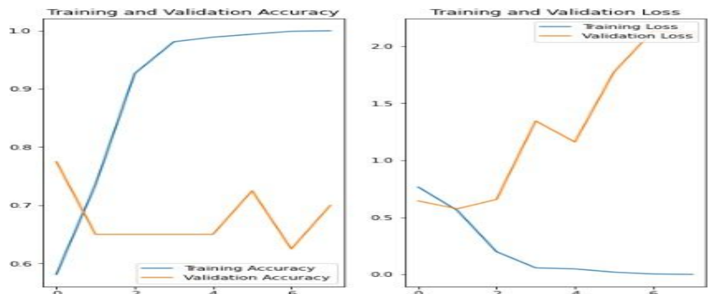

Fig. 9 Training and Validation Curve

A Precision Recall Curve is obtained. The Area Under the Curve (AUC) is calculated which is 0.911.

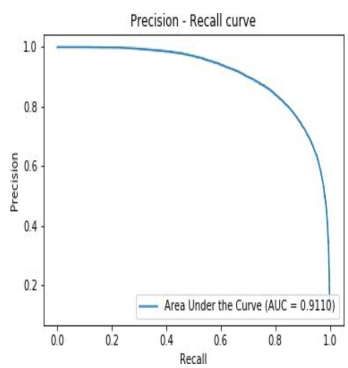

Fig. 10 Precision-Recall Curve

A Receiver Operating Characteristic curve is obtained. The Area Under the Curve (AUC) is calculated which is 0.9855.

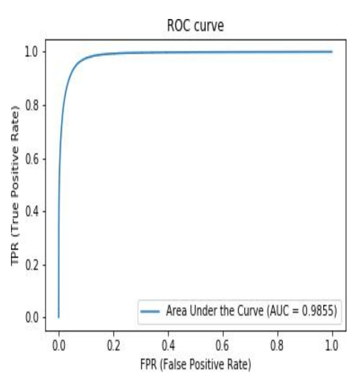

Fig. 11 ROC Curve

V. CONCLUSIONS AND FUTURE WORK

The CNN-based segmentation of retinal blood vessels has created great interest over the last 5 years for many researchers. Many models were designed to resolve this task but some problems concerning the retinal fundus image, especially the detection of small vessels, were not resolved. Precise identification of vessels has played a significant role in helping the ophthalmologist assess a disease's progress and prescribe prompt treatment. The classification system proposed in this paper is based on CNN and the evaluation was done on the Classroom Dataset. The retinal vessel segmentation system proposed in this study, is based on patch-based learning technology and the U-net. This method was evaluated on the DRIVE database and was found to be 95% accurate. The reported performance was better or comparable to other existing methods, based on conventional imaging techniques or CNN-based methods.

There is room for improvement in work in the future. The future work involves the use of large databases such that validation accuracy of the classifier can be enhanced which is around 64% in our system. The outcomes from the different classification models can be compared and the best one could be chosen. Also, the segmentation can be performed on other biomedical images.

VI. ACKNOWLEDGMENT

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REFERENCES

[1] Toufique Ahmed Soomro, Ahmed J. Afifi, Ahmed Ali Shah, Shafiullah Soomro, Gulsher Ali Baloch, Lihong Zheng, Ming Yin and Junbin Gao, “Impact of Image Enhancement Technique on CNN Model for Retinal Blood Vessels Segmentation”, volume:7|Journal Article | Publisher: IEEE, 2019

[2] Zhongming Luo, Yu Zhang, Lei Zhou, Binge Zhang, Jianan Luo and Haidin Wu, “Micro-Vessel Image Segmentation based on the AD- UNet Model”, volume:7|Journal | Article Publisher: IEEE, 2019

[3] Sehrish Qummar, Fiaz Gul Khan, Sajid Shah, Ahmad Khan, Shahaboddin Shamshirband, Zia Ur Rehman, Iftikhar Ahmed Khan and Waqas Jadoon, “A Deep-Learning Ensemble Approach for Diabetic Retinopathy Detection”, volume:7|Journal Article | Publisher: IEEE, 2019

[4] Dhimas Arief Dharmawan and Boon Poh Ng, “A New Two-Dimensional Matched Filter Based on the Modified Chebyshev Type 1 Function for Retinal Vessels Detection”, 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2017

[5] Mandalina Savu, Dan Popescu, Loretta Ichim, “Blood Vessel Segmentation in Eye Fundus Images”, International Conference on Smart Systems and Technologies, 2017

[6] Duoduo Gou, Tong Ma, Ying Wei, “A Novel Retinal Vessel Extraction Method based on Dynamic Scales Allocation” , 2nd International Conference on Image, Vision and Computing 2017

[7] A.Elbalaoui, M.Fakir, K.Taifi, A.Merbouha, “Automatic Detection of Blood Vessel in Retinal Images”, 13th International Conference Computer Graphics, Imaging and Visualization, 2016.

[8] Ambaji S Jadhav, Pushpa B Patil, “Detection of Blood Vessels in Retinal Images for Diagnosis of Diabetics”, Proceedings of the 2nd International Conference on Inventive Systems and Control (ICISC 2018)