Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 2, No. 1, February : 2023

DIABETIC RETINOPATHY STAGES PREDICTION USING DEEP LEARNING

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ABSTRACT

Retinal Blood Vessel Segmentation in Fundus images is a field of study which relies on computational models to isolate the blood vessels from a Retinal Image. The primary difficulty addressed in past literature is the formulation of a uniform solution that can segment different types of blood vessels having different amount of contrast. Our method proposed in this project is based on the approach of multiple patch size usage for segmentation using a Neural Network. The approach takes as input three different patch sizes for each pixel location which is passed through individual Convolutional Neural Network. The obtained algorithm is evaluated with the publicly available DRIVE, CHASE and STARE datasets, containing retinal images frequently used for this goal. The performance of the proposed system is calculated in terms of detection accuracy, sensitivity, specificity. Our model is compared to other vessel segmentation models with encouraging results obtained. The proposed algorithm is a suitable tool for automated retinal image analysis. The classification for each of the pixels in the image is finally combined to arrive at the final segmented image of the blood vessels in the Fundus image is normal or abnormal and the stage is also predicted. The accuracy obtained for the proposed algorithm is better in our work. Our work is implemented using MATLAB version 2019 or above.

Keywords: Diabetic Retinopathy (DR), Deep Learning (DL), Convolutional Neural Networks (CNN), Fully Connected layer (FC), Fundus images.

I. INTRODUCTION

Retinal fundus images have been widely used for diagnosis, screening and treatment of cardiovascular and ophthalmologic diseases, including age-related macular degeneration(AMD), diabetic retinopathy(DR), glaucoma, hypertension, arteriosclerosis and choroidal neovascularization, among which AMD and DR have been considered as two leading causes of blindness. Vessel segmentation is a basic step for the quantitative analysis of retinal fundus images. The segmented vascular tree can be used to extract the morphological attributes of blood vessels, such as length, width, branching and angles. Moreover, the vascular tree has been adopted in multimodal retinal image registration and retinal mosaic as the most stable feature in the images. In , the vascular tree is also used for biometric identification due to its uniqueness. Manual segmentation of the vascular tree in retinal images is a tedious task that requires experience and skill. In the development of a computer-assisted diagnostic system for ophthalmic disorders, automatic segmentation of retinal vessels has been accepted as a vital and challenging step. The size, shape and intensity level of retinal vessels can vary hugely in different local areas. The width of a vessel often ranges from 1 to 20 pixels, depending on both the anatomical width of the vessel and the image resolution. The existence of vessel crossing, branching and centerline reflex makes it difficult to segment the vessels accurately using artificially designed features.

Industrial Engineering Journal
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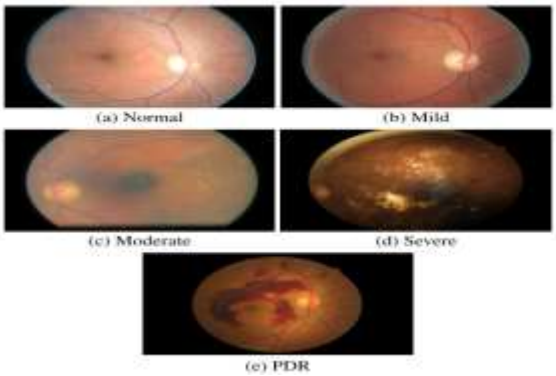

Fig 1: Different Stages of DR

Retinal image analysis is used by clinicians for the diagnosis, screening, treatment, and evaluation of various ophthalmological and cardiovascular diseases. Specifically, the analysis of retinal blood vessel is used in the screening of the diabetic retinopathy. Manual retinal blood vessels analysis is very time consuming, tedious, and prone to many errors. In order to solve these problems, the analysis of blood vessels on retinal images needs to be automated. The first step in the automation scheme is the segmentation.

Some of the published methods are a combination of other simple models known as hybrid models. They have been proposed for successful vessel segmentation. The idea behind these approaches is to take advantage of each detector. It is worth noting that, these methods are very complex and time consuming. In this project, we propose a simpler method of retinal vessel segmentation based on classical edge features and the neural network. We think that each classical edge models have its advantages which still remain to be exploited. In the next section, we present the materials and the methodology used in this work.

II. LITERATURE REVIEW

M. Ikram, Y. Ong, C. Cheung, T. Wong [1] introduced “Retinal vascular caliber measurements: clinical significance, current knowledge and future perspectives” Nevertheless, with continual development of retinal imaging techniques and newer understanding of the clinical significance of these retinal changes, there remains scope for the development of retinal vascular caliber measurements as a biomarker for vascular disease risk assessment in targeted areas and patient subgroups.

L. Klein, B.E.K. Klein, S.E. Moss, T.Y. Wong [2], proposed examining the relationship of retinopathy in persons without diabetes mellitus to the 15-year cumulative incidence of diabetes mellitus and hypertension. While controlling for other risk factors, retinopathy in nondiabetic individuals is associated with the incidence of hypertension and, in younger persons, with the incidence of diabetes mellitus.

S. Guigui, T. Lifshitz, J. Levy, [3] To review the current screening methods for diabetic retinopathy, with a focus on nonmydriatic digital fundus photography. Current research has proven that pupillary dilation is not a necessary step in the fundus examination, although it reduces the number of unnecessary referrals to ophthalmologists. Automated grading systems, while saving time and reducing human error, still need refinement before they can replace manual grading by trained ophthalmologists.

F. Zana, J.C. Klein [4] presents an algorithm based on mathematical morphology and curvature evaluation for the detection of vessel-like patterns in a noisy environment. Such patterns are very common in medical images. In order to differentiate vessels from analogous background patterns, a cross-curvature evaluation is performed.
X. Jiang, D. Mojon [5] proposed a general framework of adaptive local thresholding based on a verification-based multi threshold probing scheme. An experimental evaluation demonstrates superior performance over global thresholding and a vessel detection method recently reported in the literature. Due to its simplicity and general nature, our novel approach is expected to be applicable to a variety of other applications.
A.M. Mendonca, A. Campilho [6] presents an automated method for the segmentation of the vascular network in retinal images. This approach was tested on two publicly available databases and its results are compared with recently published methods. The results demonstrate that our algorithm outperforms other solutions and approximates the average accuracy of a human observer without a significant degradation of sensitivity and specificity.
M.S. Miri, A. Mahloojifar [7] introduced “Retinal image analysis using curvelet transform and multi-structure elements morphology by reconstruction” Retinal images can be used in several applications, such as ocular fundus operations as well as human

Industrial Engineering Journal
ISSN: 0970-2555
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recognition. Also, they play important roles in detection of some diseases in early stages, such as diabetes, which can be performed by comparison of the states of retinal blood vessels.

M.M. Fraz, S.A. Barman, P. Remagnino [8]. A unique combination of techniques for vessel centerlines detection and morphological bit plane slicing is presented to extract the blood vessel tree from the retinal images. The results demonstrate that the performance of the proposed algorithm is comparable with state-of-the-art techniques in terms of accuracy, sensitivity and specificity.

X. You, Q. Peng, Y. Yuan, Y.-M. Cheung, J. Lei [9] Retinal blood vessels analysis is of interest for medical screening, especially in the diagnosis of diabetic retinopathy.. This method is based on classical edge detection filters and artificial neural networks. Firstly, edge detection filters are applied to extract the features vector. This algorithm is a suitable tool for automated retinal image analysis.

G. Azzopardi, N. Strisciuglio, M. Vento, N. Petkov [10] introduced an novel Such a set is determined in an automatic selection process and can adapt to different applications. The results that we achieve by performing experiments on two public benchmark data sets, namely DRIVE and STARE, demonstrate the effectiveness of the proposed approach.

A. Hoover, V. Kouznetsova, M. Goldbaum [11] Describes an automated method to locate and outline blood vessels in images of the ocular fundus.The authors evaluate their method using hand-labeled ground truth segmentations of 20 images. They are making all their images and hand labelings publicly available for interested researchers to use in evaluating related methods.

B.S. Lam, Y. Gao, A.W.-C. Liew [12] The structure and appearance of the blood vessel network in retinal fundus images is an essential part of diagnosing various problems associated with the eyes, such as diabetes and hypertension.

L.C. Rodrigues, M. Marengoni M [14] Segmentation of vessel in retinal fundus images is a primary step for the clinical identification for specific eye diseases. Fast bilateral filter is an advanced version of bilateral filter that regulates the contrast while preserving the edges. Experimental results illustrate that the fusion algorithm preserved the advantages of the both and provides better result. The results demonstrate that the recommended method outperforms the traditional approaches.

S. Chaudhuri, S. Chatterjee, N. Katz, M. Nelson, M. Goldbaum [15] “Detection of blood vessels in retinal images using two-dimensional matched filters”. Various issues related to the implementation of these matched filters are discussed. The results are compared to those obtained with other methods.

T.B. Saha, D. Tchiotsop, R. Tchinda, G. Kenné [17] Parasites live in a host and get its food from or at the expensive of that host. The extracted parasite is then resized to 12x12 image features vector. For dimensionality reduction, the principal component analysis basis projection has been used. 12x12 extracted features were orthogonalized into two principal components variables that consist the input vector of the PNN.

P. Liskowski, K. Krawiec [22]“Segmenting retinal blood vessels with deep neural networks” The condition of the vascular network of human eye is an important diagnostic factor in ophthalmology.The method is also resistant to the phenomenon of central vessel reflex, sensitive in detection of fine vessels (sensitivity > 0:87), and fares well on pathological cases.

H. Fu, Y. Xu, D.W.K. Wong, J. Liu, [23] retinal vessel segmentation technology has become an important component for disease screening and diagnosing in clinical medicine. With co-constraints between pixels, the proposed DSSRN obtains better results. Finally, we show that our proposed method obtains the state-of-the-art vessel segmentation performance on all three benchmarks, DRIVE, STARE, and CHASE_DB1.

We think that each classical edge models have its advantages which remain to be exploited. In the next section, we present the materials and the methodology used in this work. Chapter III describes the proposed method. In section IV, experimental results and discussion are provided. Finally, this project is concluded in section V.

Industrial Engineering Journal
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III. PROPOSED SYSTEM

To overcome the problems with the existing system, the proposed methodology uses a deep learning technique to handle the irregular and unlabelled, high number of fundus images. Meanwhile, the deep learning techniques and algorithms are based on human-like approaches that are reliable and cost reducing, and time reducing methods. The sensitivity while considering the accuracy is also very high compared to other models when training the architecture with the fundus images (unlabelled data as well). All algorithms have been developed in the MATLAB environment. The architecture of our system is shown in Fig 2. As presented in this figure, a feature vector is extracted from the digital image. The resulting feature vector is used as the input of the neural network. The neural network is then trained to provide the image contours corresponding to the blood vessels present in the retinal image.

We used a feature vector with eight measures characterizing each pixel. From this simple principle, several convolution masks have been developed to detect the outlines of an image. The operators generally use at least two masks to perform the derivative in the abscissa and the ordinate directions. These masks are such that the sum of their coefficients is zero, so that they give a zero value in the areas without edges. The most used are the masks of Roberts, Prewitt and Sobel.

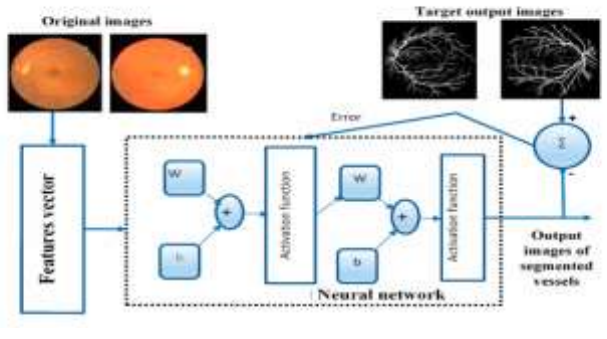

Fig. 2. Block diagram of the Proposed System.

3.1. Features Vector

A given contour corresponds either to the local maximum of the first derivative of the image function, or to the zero crossing of the second derivative of the same function. In discrete form, one can obtain the second derivative by using only one mask, that of the Laplacian. In practice, Laplacian is rarely used alone, because the second derivative is extremely sensitive to noise. As with the use of the gradient operator, the idea is to first filter the image with a low pass filter before applying the Laplacian operator.

3.1.1. Pre-processing

Amongst the three RGB (Red Green Blue) components of color images, the green channel presents the best contrast to distinguish vessels from the background, while the red and blue channels are very noisy [4]. Therefore, the green channel was selected for use in the feature vector extraction process. Before applying each edge detection filter, the following technique was applied to the green channel of fundus images to improve the image quality.

To reduce the false detection of the edge of the camera opening by the derivation process, we used a method proposed in Ref. [24]. This method consists of an iterative algorithm that removes the strong contrast between the fundus of the retina and the outer region. This procedure consists of first determining the region of interest and then in iteratively increasing this ROI in order to remove the effect of its border. To learn more about this pre-processing step, see Ref. [24]. A median filter has also been applied to reduce other noise effects.

3.1.2. The Roberts Filter:

The Roberts filter is a discrete approach to the derivative of step 1 of a function. This is the gradient of the function. If I(x, y) represents a gray level of a pixel (x, y) in an image, then the amplitudes of the gradients in x and in y can be written respectively as follows:

$$G_x = I(x+1, y) - I(x, y)$$

$$G_y = I(x, y+1) - I(x, y)$$

This amounts to convolving the image with the following two filters.

$$R_x = \begin{bmatrix} 1, & 0 \\ 0, & -1 \end{bmatrix} \text{ and } R_y = \begin{bmatrix} 0, & 1 \\ -1, & 0 \end{bmatrix}$$

The amplitude of the gradient is defined by: G(x,y)=Gx2+Gy2

$$: G(x, y) = \sqrt{G_x^2 + G_y^2}$$

If the outline is straight (step), the Roberts' filters place the one pixel outline to the left or above but its thickness will be respected. However, noise can also be a sudden local variation in gray levels

(Speckle noise for example): these filters are therefore very sensitive to noise because they accentuate, by derivation, the noise present in the image. In addition, these filters gives a thick outline if it is a ramp type contour.

3.1.3. Operators of Prewitt and Sobel

The calculation of the gradient is carried out using two masks, the first making a horizontal derivative and the second a vertical derivative. The masks are given as follows for the horizontal and vertical contours respectively:

$$\mathrm{M_h} = \begin{bmatrix} -1, & 0, & 1 \\ -C, & 0, & C \\ -1, & 0, & 1 \end{bmatrix}$$

$$\mathrm{M_v} = \begin{bmatrix} -1, & -C, & -1 \\ 0, & 0, & 0 \\ 1, & C, & 1 \end{bmatrix}$$

When C = 1, they are the operators of Prewitt, when C = 2, they are those of Sobel. Compared to the previous ones, these masks have the advantage of producing two effects. In addition to calculating the gradient in one direction, these masks perform the smoothing. This smoothing makes these masks a little less sensitive to noise than the previous ones.

3.1.4. The Canny Operator

The first step is to reduce the noise of the original image before detecting its edges. The Optimal detector used by canny filter is the first derivative of the Gaussian. The gradient of a 2D Gaussian is given as follows:(8)

gx(x,y)=−xσ2e−x2+y22σ2

$$\mathrm{g_x}\left(\mathrm{x},\mathrm{y}\right) = -\frac{\mathrm{x}}{\sigma^2}\mathrm{e}^{-\frac{x^2+y^2}{2\sigma^2}}$$

$$\mathrm{g_y}\left(\mathrm{x},\mathrm{y}\right) = -\frac{\mathrm{y}}{\sigma^2}\mathrm{e}^{-\frac{x^2+y^2}{2\sigma^2}}$$

Where σ determines the degree of smoothing. Mask size increases with the value of σ.

3.1.5. The Laplacian of Gaussian operator

The second derivative is therefore determined by the Laplacian calculus. To reduce the noise effect, the image is first smoothed with a low-pass filter. In the case of the Laplacian of Gaussian, the low-pass filter is chosen to be a Gaussian [11].

The following matrix gives a 5 × 5 Laplacian of gaussian mask, obtained from the MATLAB environment using the “fspecial” function, with σ = 1.4142.

$$\mathrm{G} = \begin{bmatrix} 0.0251 & 0.0193 & 0.0127 & 0.0193 & 0.0251 \\ 0.0193 & -0.0153 & -0.0412 & -0.0153 & 0.0193 \\ 0.0127 & -0.0412 & -0.0795 & -0.0412 & 0.0127 \\ 0.0193 & -0.0153 & -0.0412 & -0.0153 & 0.0193 \\ 0.0251 & 0.0193 & 0.0127 & 0.0193 & 0.0251 \end{bmatrix}$$

3.1.6. Mathematical morphology

The main problem with the derivative-based method is the fragmentation of the resulting contour. The morphological filter can however help to solve this problem. Morphological operators combine images with small matrices, made up of 0 or 1, called structuring elements. Structuring elements are analogous to convolution masks. The two basic operators of mathematical morphology are erosion and dilation. Let us consider a small-dimensional structuring element B and the grayscale image I. The dilatation of I by a binary image B (the structuring element) noted I⨁B is defined by the following equation, for a pixel X:

$$\forall X, (I \oplus B)(X) = \max_{p \in B} I(X + p)$$

The new value of a pixel obtained after dilatation is given by the maximum value of the pixels under the structuring element. In other words, the dilatation of I by B is the set consisting of all the structuring elements original locations where the reflected and translated B overlaps at least some portion of I [46]. Erosion is obtained in a similar way to dilation by replacing max by min. The erosion of a grayscale image I by the structuring element B denoted by I⨀B is defined as follows:

$$\forall X, (I \odot B)(X) = \min_{p \in B} I(X + p)$$

In other words, erosion of I by B is the set of all the structuring elements original locations where the translated B has no overlap with the background of I [16].

Erosion and dilation are two opposite operations of mathematical morphology. While the filters seen so far focus on changing the grayscale of pixels, the mathematical morphology seeks to change the shape of the objects. The morphological opening operation is an erosion followed by a dilation, using the same structuring element for both operations. We therefore obtain nine structure elements for nine results of erosion, dilatation and the same for the top-hat filtering. The mean value of each is used here so as to enhance all vessels

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 2, No. 1, February : 2023

independently to their direction.

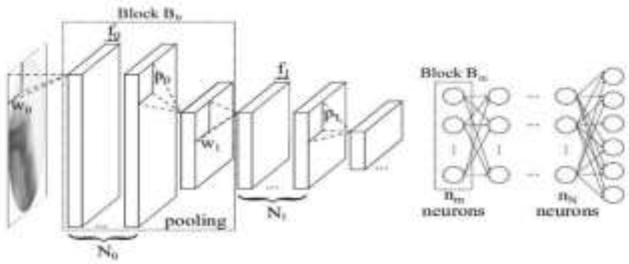

Fig 3. Pictorial representation of Convolutional Network

3.2. Neural Network:

Feed-forward networks also called MLP (Multi-Layer Perceptron) consists of a series of neural layers. The first layer has a connection from the network input meanwhile subsequent layers have a connection from the previous layer. The last layer produces the output of the network. The cascade feed-forward neural network (CFNN) is a variant of feed-forward network which has additional connections from the input to each layer, and from each layer to all subsequent layers.

Our artificial neural network structure is presented in Fig 4. It is a cascade feed-forward neural network composed of an input layer, an output layer and four hidden layers. The first hidden layer has eight neurons with hyperbolic tangent sigmoid as a transfer function. The other hidden layers have ten neurons each. The hidden layer 2 and the hidden layer 4 use hyperbolic tangent sigmoid as the transfer function. Log-sigmoid transfer function is used for the hidden layer 3.

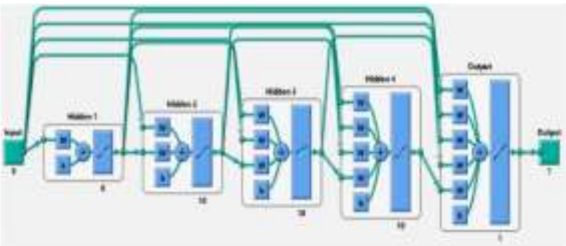

Fig. 4. Selected Neural network Topology.

For a MLP with n neurons in the input layer, k neuron in a hidden layer and one in the output layer, its mathematical equation can be written as follows:

$$y = f^0\left(b_0 + \sum_{j=1}^{k} w_j^0 f_j^h \left(b_j + \sum_{i=1}^{n} w_{ij}^h x_i\right)\right)$$

Where f0 is the activation function of the output layer, fjh is the activation of the hidden layer j, xi represents the input, y is the output. b0 is the bias on the output and bj is the bias on the hidden layer j. From the equation of the MLP, the equation formed from the CFNN model can be deduced.

As mentioned in Fig 4., the input is the set of features that would allow the CFNN to distinguish and recognize the retinal blood vessels form as a contour and something else as no contour. The set of features used are those presented in the previous section. The output y gives a value close to 1 for a detected vessel pixel and 0 for a non-detected one. To perform any task related to image processing, it is mandatory to perform the preprocessing beforehand to make the images suitable for the input data. The images contain artifacts and some of them are out of focus, underexposed, or overexposed, etc. Also, some of the images have low brightness or low lightning conditions and thus making it difficult to assess the difference between the images as well as the increase in the risk of misjudgement.

3.2.1. Relation between Artificial Neural Network and Biological Neural Network:

The term **"Artificial Neural Network"** is derived from Biological neural networks that develop the structure of a human brain. Similar to the human brain that has neurons interconnected to one another, artificial neural networks also have neurons that are interconnected to one another in various layers of the networks. These neurons are known as nodes.

Biological Neural Network	Artificial Neural Network
Dendrites	Inputs
Cell nucleus	Nodes
Synapse	Weights
Axon	Output

Table 1: Relation between Artificial Neural Network and Biological Neural Network

There are around 1000 billion neurons in the human brain. Each neuron has an association point somewhere in the range of 1,000 and 100,000. In the human brain, data is stored in such a manner as to be distributed, and we can extract more than one piece of this data when necessary, from our memory parallelly. We can say that the human brain is made up of incredibly amazing parallel

Industrial Engineering Journal
ISSN: 0970-2555
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processors.

IV. EXPERIMENTAL RESULTS

Here the layers of CNN were used and showcased in an orderly manner. The input image of iris is shown in Fig 8. Whereas the output feature extraction of the whole process is shown in fig 9 with classification.

The Algorithm:

Fig 5: Layers of CNN (1)

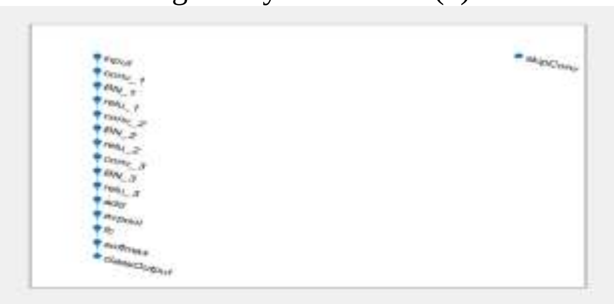

Fig 6. Layers of CNN(2)

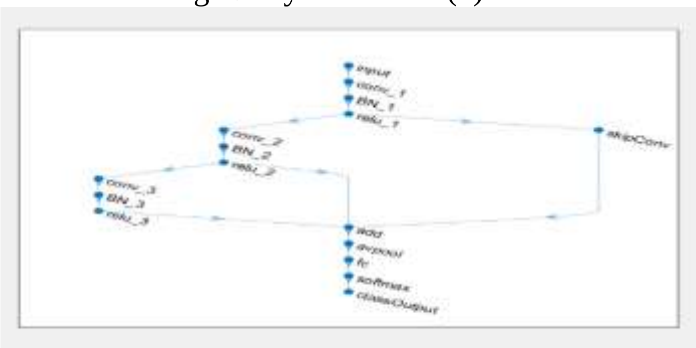

Fig 7. Layers of CNN(3)

Pre-Processing Process:

Fig 8. Input Image

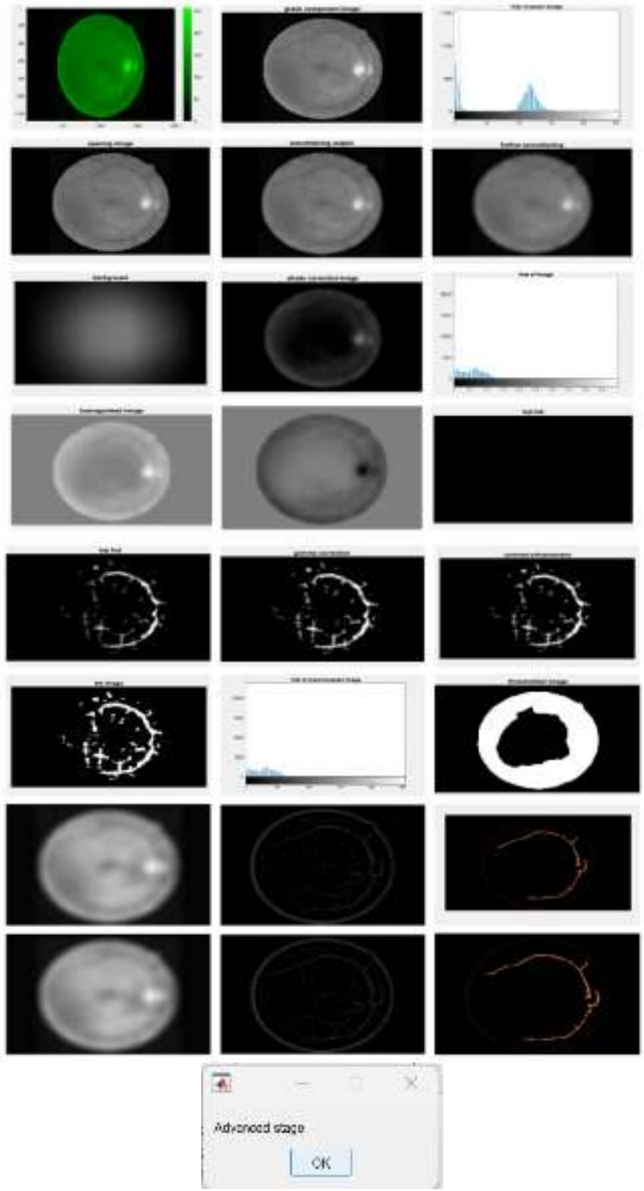

Fig 9 Stage Prediction

4.3 Accuracy:

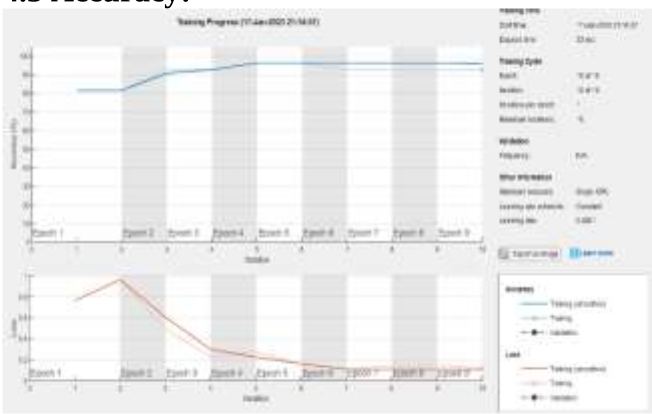

Fig 10. Accuracy Prediction

In Fig 10. The training accuracy of the CNN is done along with epochs, whereas the training progress of accuracy with MSE plot is shown.

V. CONCLUSION

In this project, we proposed a novel retinal vessel segmentation method based on classical edge detectors and the neural network. Automated screening systems or detection systems are used to dramatically reduce the amount of time consumed to determine the disease while saving the effort and costs for clinical experts or "ophthalmologists" and results in the better treatment of patients. Just like many other methods, the obtained sensitivity remains to be improved. The Automated techniques for Diabetic Retinopathy detection take up an important action in recognizing the retinopathy at a dawning stage. The "DR stages" are basically built on the type of abnormalities that can be seen on the retina. In recent years, it has been stated that CNNs can be grouped into the set of methods that are used to detect diabetes. CNNs are always an efficient technique that can leverage a large number of images that have been gathered by the ophthalmologists for the diagnosis, but also with various pixel size and inconsistency. The "high variance and low bias" of these architectures allow the CNN to recognize a vast range of non-diabetic diseases as well and such new techniques are used to bring a revolution in the medical industry and help the doctors as well as the patients.

For future work, we believe that variation in neural network architectures could be developed to further improve the results obtained by reducing spurious detections in vessel segmentation.

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