Detection of Diabetic Retinopathy using Blood Vessels

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***Abstract*— Diabetes is one of the main threats to human health in present century. Prolonged diabetes can lead to various ophthalmic disorders like glaucoma and diabetic retinopathy. Diabetic Retinopathy (DR) is caused by chronic uncontrolled hyperglycemia and is affecting eyes. If left untreated at an incipient stage, diabetic retinopathy can affect whole eye and can lead to vision loss. Diabetic Retinopathy has no prior symptoms. Hence the identification of the diseased condition at its earlier stage is utmost important. Diabetic Retinopathy is a degenerative eye disease characterized by abnormal blood vessel growth stimulated by increased blood glucose level which eventually leads to detached retina. Diabetic Retinopathy has no earlier symptoms and it can ultimately lead to vision loss. The major feature to be extracted is blood vessels. Three approaches namely, thresholding, neural network based approaches. The simulation platform is Matlab 2014a. The average value of specificity is 0.96 and false positive fraction is 0.08.These parameters reveal the efficiency of the method. Comparing to other two methods, optmisation of parameters using bee colony optimization yields the best result.**

Keywords—Thresholding, Neural Network, Bee colony opptimisation, Diabetic Retinopathy

I. INTRODUCTION

Currently there are a number of automatic systems developed for the detection of various eye diseases like diabetic retinopathy. To segment vessels in retinal images, several classes of methods have been commonly used such as matched filters, vessel tracking, morphological processing, region growing, multi scale, supervised and adaptive thresholding approaches. Processing of large data and classification of data is much difficult using other methods. The major challenges in the detection of blood vessel lie in:

1. Extraction of minute blood vessels.
2. Extracted outputs verification by an ophthalmologist.
3. Proper elimination of optic disc.
4. Elimination of optical disc is needed as the border of the disc appears as a blood vessel. To avoid dilemma, the optic disc should be detected and removed before blood vessels are extracted.
5. Blood vessels should be separated from hemorrhages, and micro aneurysms.

II. METHODS FOR EXTRACTION OF BLOOD VESSELS

A. Thresholding based method

The detection of minute blood vessels to detect diabetic retinopathy and to classify the disease severity is addressed.

Inputs

Input images for the extraction of blood vessels have been obtained from DRIVE database. It contains 40 images, their masks and the ground truth images.

Preprocessing

Input retinal images from the database have been used to extract the green channel only. Green channel has greater contrast for the blood vessel from their background. Images in green bands show vessel structures most reliably. The histogram of the green channel reveals this. The output images from blood vessel extraction were processed to get clearer contours of the vessels. The extraction of green channel can be illustrated as

$$I = [I_R \;\; I_G \;\; I_B] \tag{1}$$

Pre-processing will remove the errors incurred during the acquisition of the the image as well as it reduces the effect of brightness. The noise in the image is removed by using Gaussian Low Pass filtering. The Gaussian low pass filter is given by

$$I_{ga}(x , y)=I_g (x , y) * g (x , y) \tag{2}$$

The operation is done is convolution of green channel with the Gaussian kernel, which is given by

$$g (x , y)= \frac{1}{2\pi\sigma 2} e^{\frac{x2+y2}{2\sigma 2}} \tag{3}$$

The image after the removal of noise undergo contrast enhancement. Contrast of the image can be enhanced as to detect the blood vessels and extract them more clearly. Enhancement of the image is done as

$$I_E =255 \frac{Iga-Iga,max}{Iga,max-Iga,min} \tag{4}$$

Feature Extraction

The determination of blood vessel structure is of great importance since the variation in the structure determines the diseased condition. The extraction of the blood vessels from the enhanced image is done by using morphological operators. Morphological operations such as tophat operation and bottom hat operation are done to choose the candidate blood vessels. Morphological operators operate on the image based on the structuring element used. Structuring element can be line, diamond, disc etc. Here disc shaped structuring element is used. Top hat operation highlights the finer details and its operation is given by

$$F_T = I_E - (I_E \bullet \text{€}_i)$$

where €_i denotes the structuring element and $\bullet$ denotes opening operation. The top hat operated image is then added to the green component. This is given as

$$I_D = F_T + I_G$$

The top hat transformed image then undergoes bottom hat transformation. The bottom hat transformation highlights the background. For the bottom hat transformation also the same structuring element has been used. The expression for bottom hat transform is given by

$$F_B = (I_E \circ \text{€}_i) - I_E$$

Enhanced blood vessels are obtained by subtracting the bottom hat transformed from the enhanced bottom hat transformed image. This operation can be expressed mathematically as

$$I_\Psi = F_B - I_D$$

After performing these operations enhanced blood vessels are obtained.

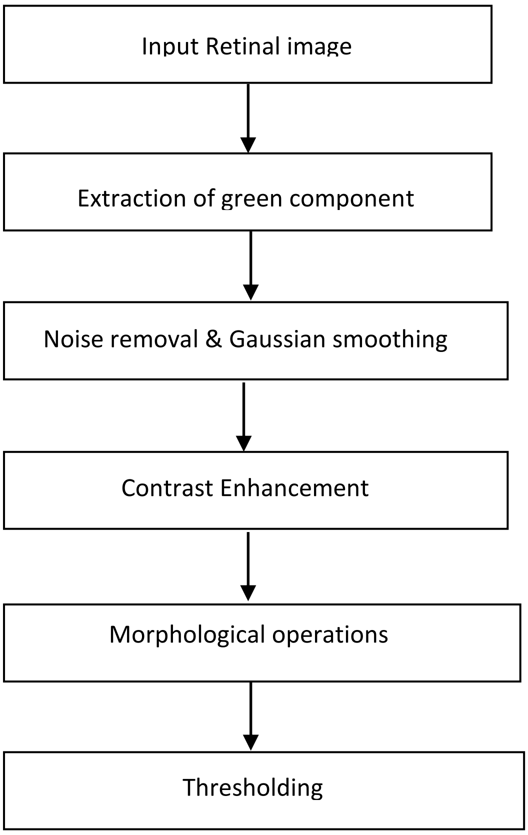


Fig 1.Block diagram for extraction of blood vessels using thresholding.

Classification

Classification of the image into blood vessel region and non-blood vessel region is possible through a number of methods. Segmentation based on the thresholding approach has been used here. Thresholding is the simplest approach for segmentation of the image into blood vessels region and non-blood vessel region. The threshold for the classification of the image is chosen in such a manner that the classification of the regions is done clearly. The regions below the threshold is classified into a region and the regions above the threshold is classified into another region. Thus, the extraction of blood vessels is done.

B. Neural network based approach

Input

The images used for the detection of blood vessels were taken from the DRIVE database. It contains 40 images and their ground truths which can be used for the detection of blood vessels.

Methodology

The detection of blood vessels are done using the neural network. Artificial neural networks are a recently developed technique according to the elementary principle of operation of human brain. ANN is a computational system inspired by structure, processing method and learning ability of human brain. The main elements of ANN include neuron-like processing elements, large number of weight elements and distributed knowledge over the connection through suitable learning process. Different algorithm used in neural network research includes supervised learning algorithm, unsupervised learning algorithm and hybrid learning algorithm.

Supervised learning algorithm provided with correct answer for every input pattern and weights are determined to have output as close as possible to correct answer. One of the examples of supervised learning is Back propagation algorithm.

Unsupervised learning algorithm doesn't require correct answer with each of the input pattern. One of the examples of unsupervised learning is Kohonen algorithm.

Hybrid algorithm combines the advantage of both supervised and unsupervised learning algorithm. That is weight are determined partly through supervised and rest through unsupervised learning.

The choice of network depends mainly on the problem to be solved the network mainly includes three layers one input layer, one output layer and at least one hidden layer. The most frequently used algorithm in neural network research is back propagation algorithm. In order to limit the computation time, the network is restricted to one hidden layer but this is adopted only when the results are satisfactory. The figure below shows the entire architecture of neural network especially for back propagation algorithm. The main applications of ANN include pattern clustering, classification, function approximation, feature recognition, forecasting, content-addressable memory etc.

Neural network comprises of three or more neuron layers such as input layer, hidden layer and output layer.

Let (X_{1},X_{2},.........X_{n}) are independent variables coded as input signal. The input layer consists of n neurons so we have n independent variables. The number of neurons chosen for hidden layer is selected randomly by the user depending upon the problem to be solved. Finally, the output layer consists of n neurons but they are dependent variables. Each of the connection between neurons is associated with a weight factor. This weight is updated by successive iterations of the algorithm during the training of the network. In the input layer, the state of the neuron is determined only by the input variable. But the other layers including hidden layer and output layer the state of the neuron is determined by the previous layer.

$$a_j = \sum_{i=1}^{n} XiWji$$

where Xi is the output value of neuron i of the previous layer, a_j is the net input of neuron j, Wji is the weight factor of the connection between neuron i and neuron j. The activation function of neurons is usually determined via a sigmoid function:

$$f(a_j) = \frac{1}{1+e^{-\,aj}}$$

Training the network

As a method of supervised learning, the back propagation technique is used to train the network. This is a common method of training neural network used along with optimization method (gradient descent algorithm. Each of the corresponding iteration will update the connection weights in order to minimize the error (error=expected value-estimated value). The weight adjustment is done from the output layer back to the input layer. The correction is made using the formula given below:

$$\Delta(Wji) = \eta\delta_j\, f(a_j)$$

where $f(a_j)$ is the output of neuron i, Δ(Wji) is the adjustment of weight between neuron j and neuron i from the previous layer, η is the learning rate, and Δ_j depends on the layer. For the output layer, Δ_j is:

$$\delta_j = (Y_j - \hat{Y}_j)\, f'_i(a_j)$$

where Y_j is the expected value ('observed value')and $\hat{Y}_j$ is the current output value ('estimated value') of neuron j. For the hidden layer, Δ_j is:

$$\Delta_j = f'_k(a_j)\sum_{i=1}^{k} \delta k\ Wjk$$

where the factor K indicates the number of neurons in the next layer. The key factor in training the network is the learning rate η. When this learning rate is low then the convergence of the weight to an optimum is very slow, when the learning rate is too high then the network can oscillate, or more seriously it can get stuck in a local minimum. To reduce these problems, a momentum term α is used and Δ (Wji) becomes:

$$\Delta(Wji) = \eta\delta_j\, f(a_j) + \alpha\,\Delta\,(W^{Prev}{}_{ji})$$

where $\alpha\ \Delta\ (W^{Prev}{}_{ji})$denotes the correction in the previous iteration. Initially α and η are chosen randomly and then they are modified according to the importance of the error by the following algorithm:

The training, performed on a representative data set, runs until the sum squared of errors (SSE) is minimized:

$$SSE = \frac{1}{2}\sum_{p=1}^{P}\sum_{j=1}^{N}(\,Ypj\ -\ \hat{Y}pj)2$$

where: Y_{pj} is the expected output value, $\hat{Y}_{pj}$ is the estimated value by the network, j=1,2,.......N is the number of records and p=1,2.......P is the number of neurons in the output layer. The structure of the network, the number of records in the data set and the number of iterations that determine the training duration.

Testing the Network

The next step after training the network is testing the network. In the test set up, the input data is fed into the classification network in which desired value are compared to network output values. The mismatching or matching of the results is used as an indication of performance of the training network.

Algorithm for classification is listed below

1. Set the training data.
2. Initialize the weight at random, choose the corresponding learning rate.
3. For each of the training data do the forward pass and then compute delta of the corresponding output.
4. Update the weights based on gradient descent algorithm.

The training of ANN is aimed at reducing the mean square error (MSE). The training requires several iterations, efficiently achieved by parallel processing.

C. Neural Network Based Approach and parameter optimisation through Bee Colony Optimization

Input

The images used for the detection of blood vessels were taken from the DRIVE database. It contains 40 images and their ground truths which can be used for the detection of blood vessels.

The optimization parameters of the neural network yields best results than choosing random parameters. There are several optimization techniques, namely, Ant Colony Optimization, Bee Colony Optimization, and Particle Swarm Optimization. Bee Colony Optimization technique has been employed here. The optimization of parameters is done based on finding the global maxima. Bee Colony optimization is based on the genetic algorithm, which is a heuristic search method. As the name suggests, the parameter optimization mimics the behaviour of bees. In genetic algorithm, the individuals in the population undergo reproduction. The best parents are chosen for the production of the new population based on their fitness values. Hence optimized parameters are obtained.

Bee Colony Optimization

The Bees Algorithm mimics the foraging strategy of honey bees to look for the best solution to an optimization problem. Each candidate solution is thought of as a food source (flower), and a population (colony) of n agents (bees) is used to search the solution space. Each time an artificial bee visits a flower (lands on a solution), it evaluates its profitability (fitness).The Bees Algorithm consists of an initialization procedure and a main search cycle which is iterated for a given number T of times, or until a solution of acceptable fitness is found. Each search cycle is composed of five procedures:

- recruitment
- local search
- neighbourhood shrinking
- site abandonment
- global search

The main steps of the algorithm are given below:

1. Initial food sources are produced for all employed bees
2. REPEAT
3. Each employed bee goes to a food source in her memory and determines a neighbour source, then evaluates its nectar amount and dances in the hive
4. Each onlooker watches the dance of employed bees and chooses one of their sources depending on the dances, and then goes to that source. After choosing a neighbour around that, she evaluates its nectar amount
5. Abandoned food sources are determined and are replaced with the new food sources discovered by scouts
6. The best food source found so far is registered
7. UNTIL (requirements are met)

Hence the blood vessels are efficiently detected.

III. RESULTS

The performance of the approaches used in this study is evaluated in order to find the method's accuracy. The performance is evaluated using the following parameters.
True Positive (T_P): It is defined as the number of blood vessels pixels correctly identified as blood vessels pixels.
True Negative (T_N): it is defined as the number of non blood vessels pixels correctly identified as non blood vessels pixels.
False Negative (F_N): it is defined as the number of blood vessels pixels identified as non blood vessels pixels.
False Positive (F_P): it is defined as the number of non blood vessels pixels identified as blood vessels pixels.
Based on the above mentioned parameters, sensitivity, false positive fraction (FPF) and accuracy are computed. Sensitivity is the percentage of the actual blood vessel pixels that are detected and the accuracy is calculated by the ratio of the number of correctly classified pixels to the total number of pixels in the image.

The mathematical expression for the parameters are given by

$$\text{Sensitivity} = \frac{T_P}{F_N + T_P}$$

$$\text{FPF} = \frac{F_P}{F_P + T_N}$$

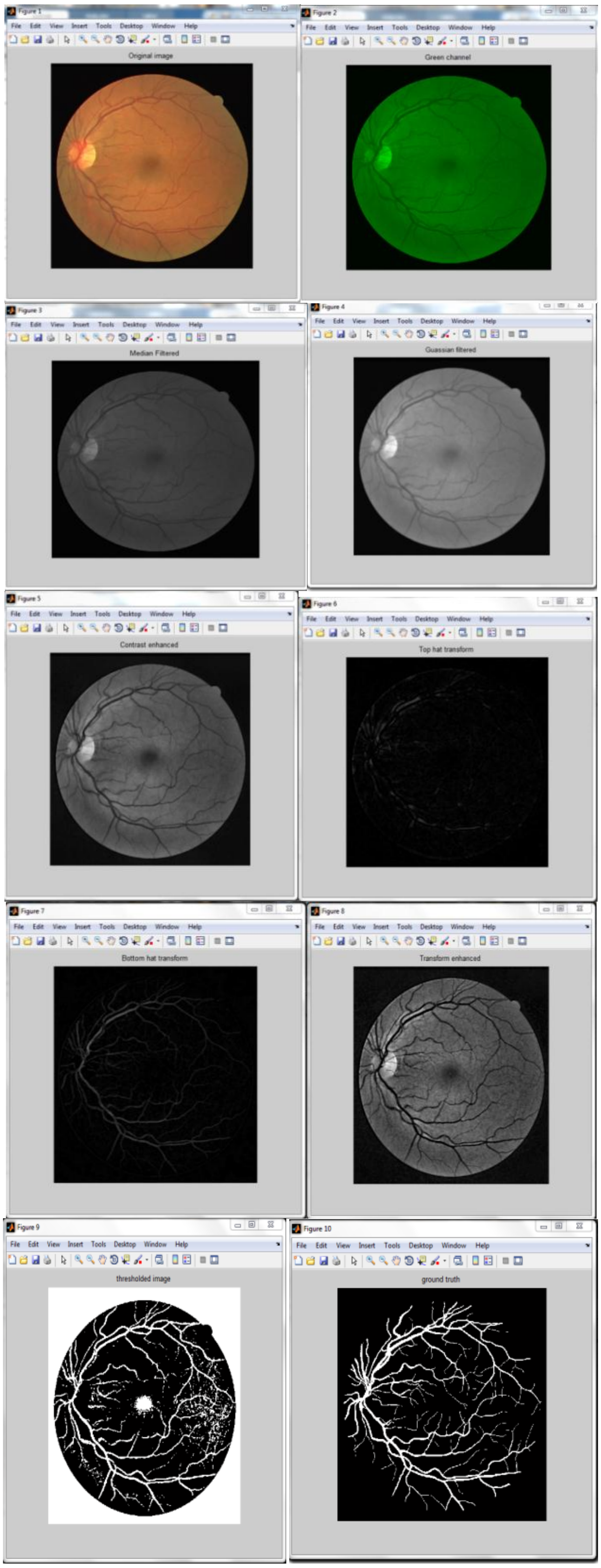
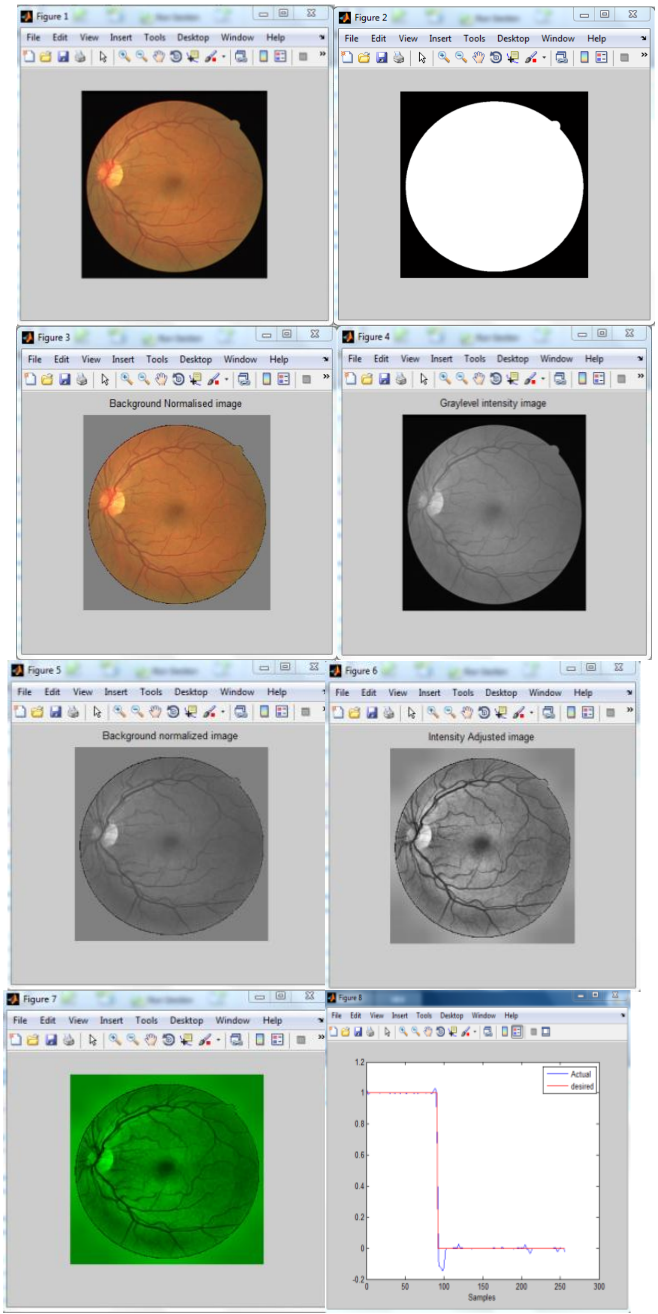
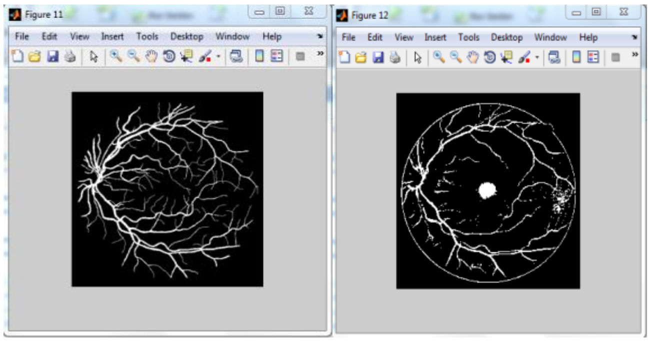


Fig 2.shows the result obtained after thresholding.2(a)Original image.2(b)Green channel extracted image.2(c) Median filtered image 2(d) Gaussian filtered image 2(e) Contrast enhanced 2(f) Top hat operation 2(g) Bottom hat operation 2(h) Transform enhanced 2(i) Thresholded output 2(j) Ground truth

Table 1. Parameters obtained after applying thresholding

Inputs	Sens	spes	fpf	acc
img1	0.7421	0.9631	0.0369	0.9434
img2	0.7056	0.9726	0.0274	0.9453
img3	0.8165	0.807	0.193	0.8079
img4	0.7124	0.8869	0.1131	0.8708
img5	0.789	0.8222	0.1778	0.8191
img6	0.6732	0.9101	0.0899	0.887
img7	0.7014	0.8873	0.1127	0.8703
img8	0.7532	0.8468	0.1532	0.8387
img9	0.5609	0.9712	0.0288	0.9379
img10	0.7927	0.8055	0.1945	0.8044
Avg	0.7247	0.88727	0.11273	0.87248





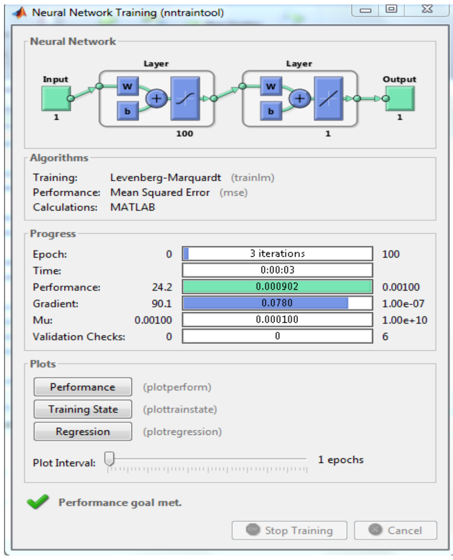
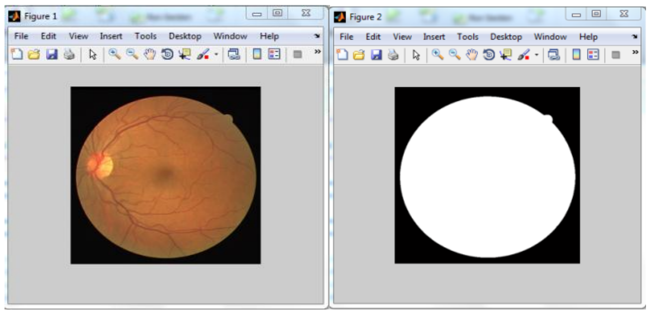
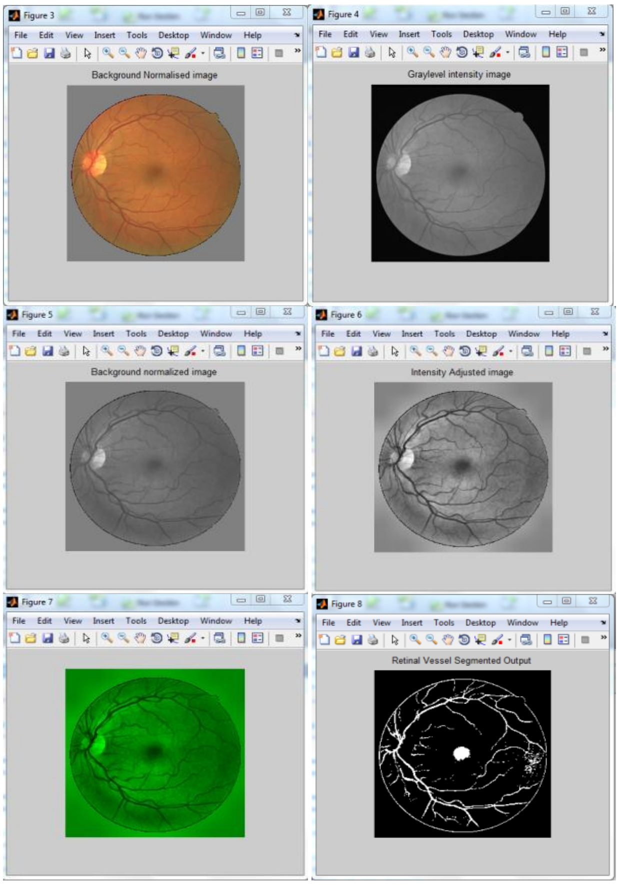


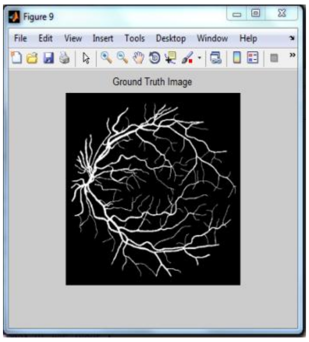
Fig 3.shows the result obtained after applying neural network.3(a)Original image.3(b) Mask.3(c) Back ground normalised 3(d) Graylevel image 3(e) Intensity normalised image 3(f Intensity adjusted image 3(g) Green channel 3(h) Training error 3(i) Ground truth 3(j) Output 3(k) NN training

Table 2. Parameters obtained after applying neural network

Inputs	Sens	spes	fpf	acc
img1	0.8509	0.9784	0.0216	0.9727
img2	0.8598	0.9758	0.0242	0.9682
img3	0.9333	0.6884	0.3116	0.7055
img4	0.8492	0.8042	0.1958	0.8069
img5	0.9264	0.7605	0.2395	0.7693
img6	0.8117	0.8902	0.1098	0.8857
img7	0.857	0.8262	0.1738	0.8277
img8	0.8598	0.7981	0.2019	0.8011
img9	0.5506	0.9864	0.0136	0.9693
img10	0.9287	0.6284	0.3716	0.6416
Avg	0.84274	0.83366	0.16634	0.8348







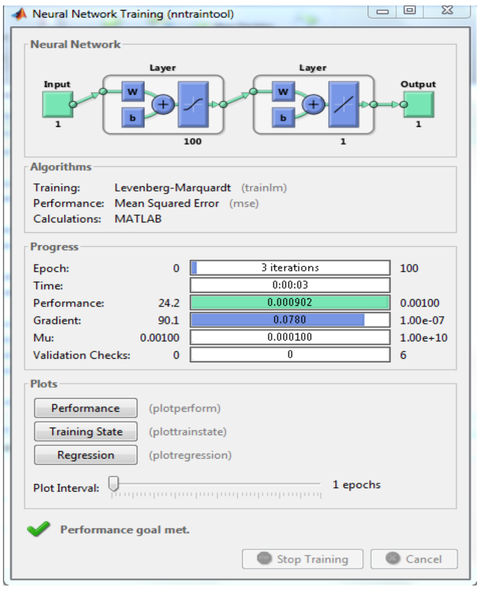


Fig 4.shows the result obtained after applying neural network and bee colony optimisation.4(a)Original image.4(b) Mask.4(c) Back ground normalised 4(d) Graylevel image 4(e) Intensity normalised image4(f)Intensity adjusted image 4(g) Green channel 4(h) Training error 4(i) Ground truth 4(j) Output 4(k) NN training

Table 3. Parameters obtained after applying neural network and bee colony optimisation

Inputs	Sens	Spes	fpf	Acc
img1	0.8411	0.9802	0.0198	0.974
img2	0.8498	0.9778	0.0222	0.9694
img3	0.928	0.7101	0.2899	0.7253
img4	0.8447	0.8184	0.1816	0.82
img5	0.9206	0.7833	0.2167	0.7905
img6	0.7999	0.8984	0.1016	0.8927
img7	0.8483	0.8369	0.1631	0.8374
img8	0.8512	0.8128	0.1872	0.8147
img9	0.5313	0.9869	0.0131	0.9691
img10	0.9238	0.6471	0.3529	0.6593
Avg	0.83387	0.84519	0.15481	0.84524

For the extraction of blood vessels 40 images from DRIVE database is taken. The results obtained for 10 samples are shown. The average value of specificity is 0.96 and false positive fraction is 0.08.These parameters reveal the efficiency of the method. Comparing to other two methods, optimization of parameters using bee colony optimization yields the best result.

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