Neural Network Based Retinal Blood Vessel Segmentation And Disease Identification

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Abstract- *Diabetic retinal image classification aims to conduct diabetic retinopathy automatically diagnosing, which has achieved considerable improvement by deep learning models. However, these methods all rely on sufficient network training by large scale annotated data, which is very labor-expensive in medical image labeling. This project presents a new supervised method for vessel segmentation in retinal images. This method remolds the task of segmentation as a problem of cross-modality data transformation from retinal image to vessel map. A wide and deep neural network with strong induction ability is proposed to model the transformation, and an efficient training strategy is presented. Instead of a single label of the center pixel, the network can output the label map of all pixels for a given image patch. Finally to extract retinal disease stages by comparing features using fuzzy neural networks. In this work these two parts of the network one is neural network for training. Second is fuzzy inference system which helps us improve the performance result in retinal image. The proposed method has the potential for application in image diagnosis of ophthalmologic diseases, and it may provide a new, general, high-performance computing framework for image segmentation.*

Keywords- ophthalmologic diseases, deep learning models, fuzzy neural networks,

I. INTRODUCTION

Retina is the tissue lining the interior surface of the eye which contains the light sensitive cells (photoreceptors). Photoreceptors convert light into neural signals that are carried to the brain through the optic nerves. In order to record the condition of the retina, an image of the retina (fundus image) can be obtained. A fundus camera system (retinal microscope) is usually used for capturing retinal images. Retinal image contains essential diagnostic information which assists in determining whether the retina is healthy or unhealthy. Retinal images have been widely used for diagnosing vascular and non-vascular pathology in medical society. Retinal images provide information on the changes in retinal vascular structure, which are common in diseases such as diabetes, occlusion, glaucoma, hypertension, cardiovascular disease and stroke. These diseases usually change reflectivity, tortuosity, and patterns of blood vessels. For example, hypertension changes the branching angle or tortuosity of vessels and diabetic retinopathy can lead to neovascularization i.e., development of new blood vessels. If left untreated, these medical conditions can cause sight degradation or even blindness. The early exposure of these changes is important for taking preventive measure and hence, the major vision loss can be prevented. Automatic segmentation of retinal blood vessels from retinal images would be a powerful tool for medical diagnostics. For this purpose, the segmentation method used should be as accurate and reliable as possible. The main aim of segmentation is to differentiate an object of interest and the background from an image.

The vessel segmentation methodologies were evaluated by using two publicly available databases containing the retinal images, DRIVE and STARE. The DRIVE database contains 40 retinal color images among which seven contain signs of diabetic retinopathy. The images have been captured using Canon CR5 nonmydriatic 3-CCD camera with a 45° field of view (FOV). Each image has 768 × 584 pixels with 8 bits per color channel in JPEG format. The database is divided into two groups: training set and test set, each containing 20 images. The training set contains color fundus images, the FOV masks for the images, and a set of manually segmented monochrome (black and white) ground truth images. The test set contains color fundus images, the FOV masks for the images, and two set of manually segmented monochrome ground truth images by two different specialists.

The ground truth images of the first observer were used for measuring the performance of algorithms. The STARE database for blood vessel segmentation contains 20 color retinal images among which ten contain pathology. The images have been taken using TopCon TRV-50 camera with 35° FOV. Each image has 700 × 605 pixels with 8 bits per color channel in PPM format. This database does not have separate training and test sets as in DRIVE. It also contains two sets of manually segmented monochrome ground truth images by two different specialists. The manually segmented images by the first human observer were used as the ground truth for evaluating the performance of the algorithms.

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 the two leading causes of blindness. Vessel segmentation is a basic step required 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. Pathologies in the form of lesions and exudates can further complicate the automatic segmentation. In the past decades, several methods have been proposed for the segmentation of vessels in retinal images, and they can be divided into two categories: unsupervised and supervised methods.

The unsupervised methods use filter responses or other model-based techniques to extract vessels. According to the image processing methodologies, these methods can be classified into three sub-categories: matched filtering, vessel tracking and model-based approaches. A matched filtering technique convolves a 2-D kernel with the retinal image, and the matched filter response indicates the presence of the vessel. The latest proposed method, presented by Azzopardi et al., uses a combination of shifted filter responses (COSFIRE) to detect vessels, and the average accuracy, sensitivity and specificity are 0.9442, 0.7655 and 0.9704, respectively, on the DRIVE database and 0.9563, 0.7716 and 0.9701 for the STARE database. The matched filtering methodology works well for healthy images but is prone to increased false positive rates with pathological images. Vessel tracking algorithms use local information to segment a vessel between two points. The center of the longitudinal cross-section of a vessel is determined using gray-level intensity and tortuosity. This type of method can provide highly accurate vessel widths, but they often are unable to detect vessel segments that have no seed points. The model-based approaches apply the explicit vessel models, such as vessel profile models and deformable models, to extract the retinal vessels. In profile models, the intensity of the vessel cross-section is considered as a Gaussian shape. Other profiles, such as the second-order derivative Gaussian, are also exploited to increase the segmentation accuracy with low image quality. The profile model opts to be compromised by vessel crossing and branching. More complicated deformable models, such as parametric deformable models and geometric deformable models, are also reported for vessel segmentation.

Supervised methods use extracted feature vectors to train a classifier to discriminate between vessel and non-vessel pixels. The algorithm can learn a set of rules of vessel extraction on the basis of a training set. The performance of supervised methods is usually better than that of unsupervised ones and can produce good results for healthy retinal images. Most supervised methods adopt support vector machines (SVM) or artificial neural networks (ANN) as the classifier. Compared to SVM, a multilayer neural network can model more complicated relations between the input and output. In, Marin et al. presented a neural network-based supervised methodology. They simultaneously use gray-level and moment invariant-based features to build a 7-D feature vector and utilize a multilayer feed forward neural network for training and classification. The reported accuracy, sensitivity and specificity of their method are 0.9452, 0.7067 and 0.9801, respectively, on the DRIVE database and 0.9526, 0.6944 and 0.9819 for the STARE database. The decision tree has also been used in vessel classification. Present a supervised method using an ensemble system of bagged and boosted decision trees. They utilize four techniques to extract the feature vector, including gradient vector field, morphological transformation, line feature and Gabor responses.

The average accuracy, sensitivity and specificity are improved to 0.9480, 0.7406 and 0.9807 for DRIVE and 0.9534, 0.7548 and 0.9763 for STARE. Cheng et al. use a random forest to fuse the rich information encoded in the hybrid context-aware features and achieve comparable performance to state-of-the-art methods. Most published supervised methods use artificially designed features to model the retinal vessel. However, the manual feature design is a heuristic and laborious procedure that is heavily dependent on experience and skills. Moreover, to address pathology, image noise and other complicated cases, the parameters used in the algorithm usually need to be careful adjusted.

II. LITERATURE SURVEY

This paper presents a method for automated vessel segmentation in retinal images. For each pixel in the field of view of the image, a 41-D feature vector is constructed, encoding information on the local intensity structure, spatial properties, and geometry at multiple scales. An AdaBoost classifier is trained on 789 914 gold standard examples of vessel and nonvessel pixels, then used for classifying previously unseen images. The algorithm was tested on the public digital retinal images for vessel extraction (DRIVE) set, frequently used in the literature and consisting of 40 manually labeled images with gold standard. Results were compared experimentally with those of eight algorithms as well as the additional manual segmentation provided by DRIVE. Training was conducted confined to the dedicated training set from the DRIVE database, and feature-based AdaBoost classifier (FABC) was tested on the 20 images from the test set. FABC achieved an area under the receiver operating characteristic (ROC) curve of 0.9561, in line with state-of-the-art approaches, but outperforming their accuracy (0.9597 versus 0.9473 for the nearest performer).

Automatic segmentation of retinal blood vessels has become a necessary diagnostic procedure in ophthalmology. The blood vessels consist of two types of vessels, i.e., thin vessels and wide vessels. Therefore, a segmentation method may require two different processes to treat different vessels. However, traditional segmentation algorithms hardly draw a distinction between thin and wide vessels, but deal with them together. The major problems of these methods are as follows: (1) If more emphasis is placed on the extraction of thin vessels, the wide vessels tend to be over detected; and more artificial vessels are generated, too. (2) If more attention is paid on the wide vessels, the thin and low contrast vessels are likely to be missing. To overcome these problems, a novel scheme of extracting the retinal vessels based on the radial projection and semi-supervised method is presented in this paper. The radial projection method is used to locate the vessel centerlines which include the low-contrast and narrow vessels. Further, we modify the steerable complex wavelet to provide better capability of enhancing vessels under different scales, and construct the vector feature to represent the vessel pixel by line strength. Then, semi-supervised self-training is used for extraction of the major structures of vessels. The final segmentation is obtained by the union of the two types of vessels. Our approach is tested on two publicly available databases. Experiment results show that the method can achieve improved detection of thin vessels and decrease false detection of vessels in pathological regions compared to rival solutions.

Retinal images can be used in several applications, such as ocular fundus operations as well as human 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. Intrinsic characteristics of retinal images make the blood vessel detection process difficult. Here, we proposed a new algorithm to detect the retinal blood vessels effectively. Due to the high ability of the curvelet transform in representing the edges, modification of curvelet transform coefficients to enhance the retinal image edges better prepares the image for the segmentation part. The directionality feature of the multistructure elements method makes it an effective tool in edge detection. Hence, morphology operators using multistructure elements are applied to the enhanced image in order to find the retinal image ridges. Afterward, morphological operators by reconstruction eliminate the ridges not belonging to the vessel tree while trying to preserve the thin vessels unchanged. In order to increase the efficiency of the morphological operators by reconstruction, they were applied using multistructure elements. A simple thresholding method along with connected components analysis (CCA) indicates the remained ridges belonging to vessels. Experimental results on a known database, DRIVE, and achieving to more than 94% accuracy in about 50 s for blood vessel detection, proved that the blood vessels can be effectively detected by applying our method on the retinal images.

Detecting blood vessels in retinal images with the presence of bright and dark lesions is a challenging unsolved problem. In this paper, a novel multiconcavity modeling approach is proposed to handle both healthy and unhealthy retinas simultaneously. The differentiable concavity measure is proposed to handle bright lesions in a perceptive space. The line-shape concavity measure is proposed to remove dark lesions which have an intensity structure different from the line-shaped vessels in a retina. The locally normalized concavity measure is designed to deal with unevenly distributed noise due to the spherical intensity variation in a retinal image. These concavity measures are combined together according to their statistical distributions to detect vessels in general retinal images. Very encouraging experimental results demonstrate that the proposed method consistently yields the best performance over existing state-of-the-art methods on the abnormal retinas and its accuracy outperforms the human observer, which has not been achieved by any of the state-of-the-art benchmark methods. Most importantly, unlike existing methods, the proposed method shows very attractive performances not only on healthy retinas but also on a mixture of healthy and pathological retinas.

A method is presented for automated segmentation of vessels in two-dimensional color images of the retina. This method can be used in computer analyses of retinal images, e.g., in automated screening for diabetic retinopathy. The system is based on extraction of image ridges, which coincide approximately with vessel centerlines. The ridges are used to compose primitives in the form of line elements. With the line elements an image is partitioned into patches by assigning each image pixel to the closest line element. Every line element constitutes a local coordinate frame for its corresponding patch. For every pixel, feature vectors are computed that make use of properties of the patches and the line elements. The feature vectors are classified using a NN-classifier and sequential forward feature selection. The algorithm was tested on a database consisting of 40 manually labeled images. The method achieves an area under the receiver operating characteristic curve of 0.952. The method is compared with two recently published rule-based methods of Hoover et al. and Jiang et al. The results show that our method is significantly better than the two rule-based methods (0 01). The accuracy of our method is 0.944 versus 0.947 for a second observer.

III. PROPOSED SYSTEM

The architecture of the proposed retinal recognition framework is shown in Fig 1 and it is discussed in this section. Fuzzy logic and artificial neural networks are complementary technologies in the design of intelligent system. The combination of these two technologies into an integrated system appears to be a promising path toward the development of intelligent systems capable of capturing qualities characterizing the human brain. At present many methods for image recognition are available but most of them include feature to any type of images. The proposal is divided into two phases: the training phase and the extraction or processing related to type of image. The method proposed in this paper can be applied recognition phase.

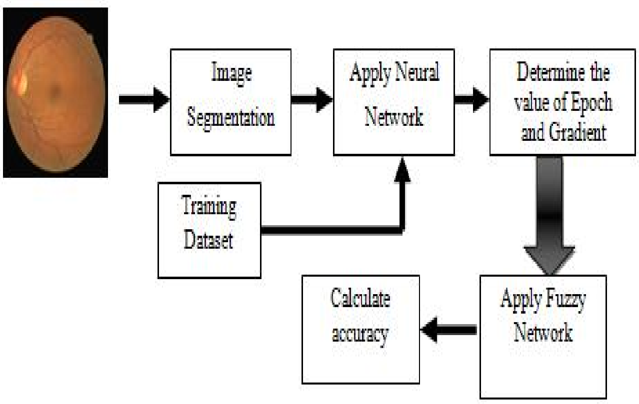

Fig 1 Proposed system architecture

Input image is taken in the .jpg format. The input image is being segmented using discrete wavelet transform. Then the segmented result is given to artificial neural networks, it classify the disease stages and produce epoch and gradient value of the input image. Then the fuzzy network calculates the accuracy of the input image.

SYSTEM MODULES

The proposed system includes three modules they are, Segmentation, Concatenation of the Input and Output, Artificial Neural Network, Fuzzy Neural Network

Segmentation

Wavelet transform is an efficient tool to represent an image. The wavelet transform allows multi-resolution analysis of an image. The wavelet transform has received attention in image processing due to its flexibility in representing non-stationary image signals. Wavelet transforms are the most powerful and widely used tool in image processing. The applications of Wavelet transforms are Image compression, such as still image compression, image denoising and watermarking. Wavelet-coding schemes at higher compression ratios avoid blocking artifacts. Because of their inherent multi –resolution nature, wavelet-coding schemes are especially suitable for applications where scalability and tolerable degradation are important.

Discrete Wavelet transforms are implemented through sub-band coding. By using DWT we can avoid time complexity. The DWT is useful in image processing because it simultaneously localise signals in time and scale. The 1-D DWT can be extended to 2-D transform using separable wavelet filters. With separable filters, applying a 1-D transform to all the rows of the input and then repeating on all of the columns can compute the 2-D transform. When one-level 2-D DWT is applied to an image, four transform coefficient sets are created. The four sets are LL, HL, LH, and HH, where the first letter corresponds to applying either a low pass or high pass filter to the rows, and the second letter refers to the filter applied to the columns.

Concatenation of the Input and Output

To use the characteristics of the denoising autoencoder to exploit the relations between the retinal image and label map, we have designed a training strategy based on concatenation of the input and output. Specifically, we concatenate the input Image x and the vessel map y in an input vector denotes concatenation), and, at the same time, we concatenate the input image and map zero in another vector

Because we attempt to obtain the label map given only the images, we set half of the training set to be and half to be while the output only consists of . Thereby, the autoencoder is forced to learn the relations between the image and the label map (similar to recovering a clean input from a corrupted one). Suppose the image patch is N*N in size and the learnt weight of the first layer of the autoencoder is then, the weight of the first layer of the proposed network can be initialized by the first half of the learnt weight: =

The denoising autoencoder has learnt a group of bases with different feature location and orientation. This pre-training procedure is important to the optimization of the network because directly learning the parameters of five layers is likely to converge in local minima. However, it must be noted that the pre-training used here is very different to unsupervised lay-wise pre-training. In the traditional initialization of a deep network, the unsupervised lay-wise pre-training learns a group of bases that can best reconstruct the input vector. In this study, the pre-training is designed to learn the mapping function f(x; w), and it can be treated as an important step in moving forward from the original image to the vessel map.

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Artificial neural network (ANNs) is a simple mathematical or neural network model that comes under machine learning. That is, the interconnection pattern exists between various neuron layers, interconnection weight updating learning process and activation function. In this artificial neural network for finger vein image classification and training for classifying whether the finger vein image is authorized or not, is defined with a collection of input neurons which are activated by the pixels of the input fingervein image. Then it is weighted and transformed by a function by changing the weights and parameters (number of neurons) involved. By that it finds the members of the class obtained. This function is called the activation function which converts the weighted input of neuron to its output activation. The other connected neurons are also get activated sequentially and continued till the output neuron is activated. Finally it finds in which class the function belongs to. This determines whether the image belongs to authorized person or un authorized person.

Fuzzy Neural Network

The proposal is divided into two phases: the training phase and the extraction or processing related to type of image. The method proposed in this paper can be applied recognition phase.

Training of the Neural Network

The training of neural network consists of following steps as shown in Fig 4.2.

The first step for training is to provide the network with data set. For this purpose identical row from the image matrix is considered as input for designing the structure.

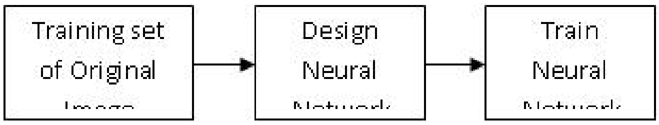


Fig 2 Training of neural network

The dataset obtained from step 1 is now used to design the neural network architecture as shown in Fig 2. The network designed has number of input equals to number of columns in the dataset matrix. Here, BPNN is working in feed forward mode. This network has a layered structure. The basic layers are input, hidden and output layer. This is different from others based on the way the weights are calculated during learning. When the numbers of hidden layers are increased, training becomes more complex. There can be more than one hidden layer in the network, but one layer is sufficient to solve purpose. The training of BPNN is done in three stages:

Feed-forward of input
Calculation of weights and error

Input layer consists of units which receives external input. There are no connections within a layer. This input is fed to the first layer of hidden units. Hidden unit apply activation function and receives weighted bias, the output of the hidden units is distributed over the next layer of hidden units. This process continues until the last layer of hidden units. The outputs are fed into a layer of output units. Though training of BPNN is very slow, once the network is trained it produce results rapidly. In the final step training of neural network is performed, after the database is created target is set corresponding to the images want to store in database. The above designed network is then trained such that output of the network well matches with the target values. Much closer the trained value, accuracy comes out to be more. Thus, for this purpose network can be trained up to 4 to 5 times. This step completes the first phase.

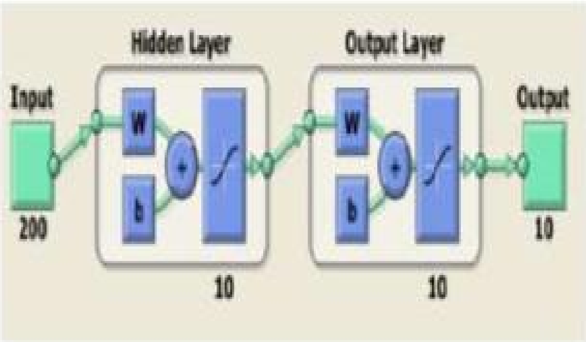


Fig 3 Designed neural network

Neuro-fuzzy Classifier

In the NFC, the feature space is partitioned into multiple fuzzy subspaces by fuzzy if-then rules. These fuzzy rules can be represented by a network structure. An NFC is a multilayer feed-forward network consisting of the following layers: input, fuzzy membership, fuzzification, defuzzification, normalization, and output. The classifier has multiple inputs and multiple outputs. Fig 3 depicts an NFC with two features and three classes. Every input is defined with three linguistic variables; thus, there are nine fuzzy rules.

Membership layer: the membership function of each input is identified in this layer. Several types of membership functions can be used. In this study, a Gaussian function is utilized, since this function has fewer parameters and smoother partial derivatives for parameters. The Gaussian membership function is defined as

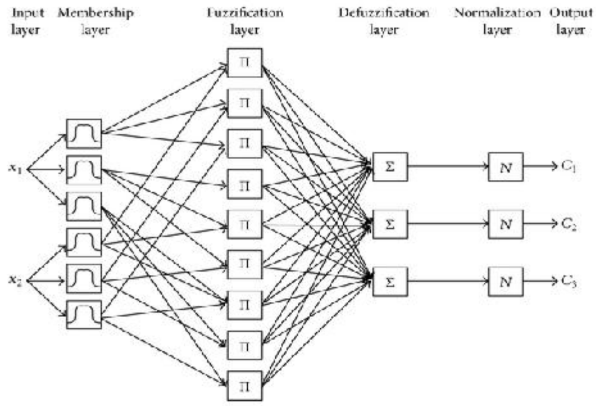


Fig 4 Neuro-fuzzy classifier

$$\mu_{ij}(x_{sj}) = exp\left(-\frac{(x_{sj} - c_{ij})^2}{2\sigma_{ij}^2}\right)$$

where $\mu_{ij}(x_{sj})$ is the membership grade of ith rule and jth feature; x_{sj} represents the sth sample and jth feature; c_{ij} and σ_{ij} are the center and the width of Gaussian function, respectively.

Fuzzification layer: each node in this layer generates a signal corresponding to the degree of fulfillment of the fuzzy rule for the x_s sample. It is called the firing strength of a fuzzy rule with respect to an object to be classified. The firing strength of the ith rule is as follows:

$$\alpha_{is} = \prod_{j=1}^{N} \mu_{ij}(x_{sj})$$

where N is the number of features.

Defuzzification layer: in this layer, weighted outputs are calculated; each rule affects each class according to their weights. If a rule controls a specific class region, the weight between that rule output and the specific class will be larger than the other weights. Otherwise, the class weights are small. The weighted output for the sth sample that belongs to the kth class is calculated as follows:

$$\beta_{sk} = \sum_{i=1}^{M} \alpha_{is} w_{ik}$$

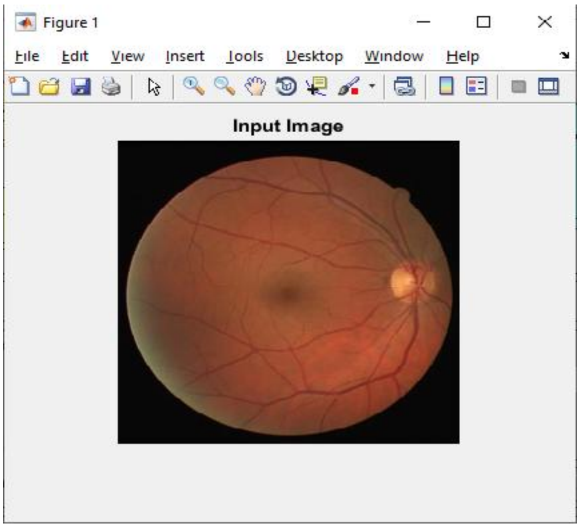
where w_{ik} denotes the degree of belonging to the kth class that is controlled by the ith rule and M represents the number of rules.

Normalization layer: the outputs of the network should be normalized, since the summation of weights may be larger than 1 in some cases

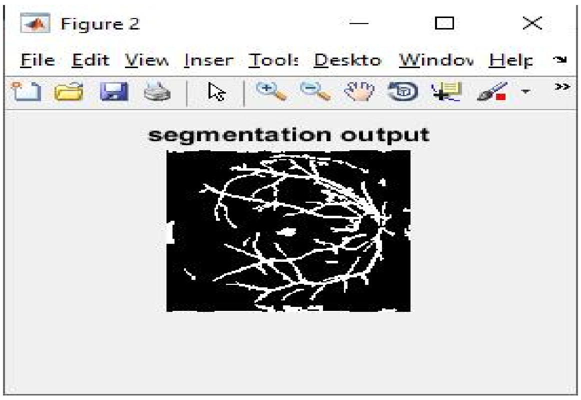
$$o_{sk} = \frac{\beta_{sk}}{\sum_{l=1}^{K} \beta_{sl}}$$

where o_{sk} denotes the normalized value of the sth sample that belongs to the kth class and K is the number of classes.

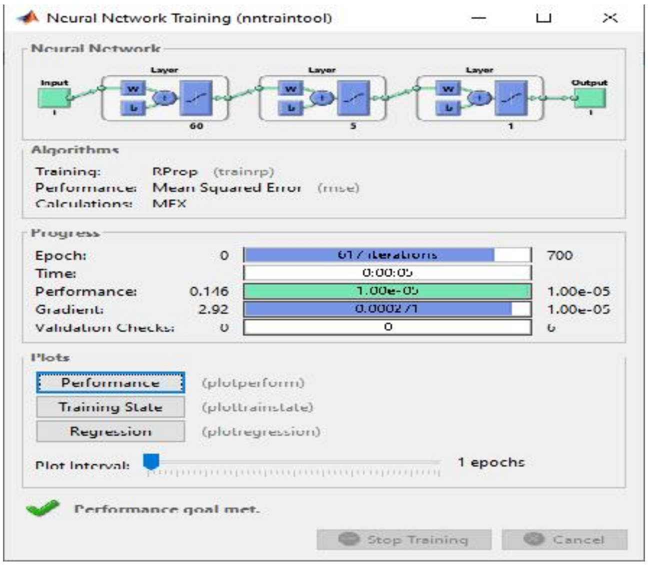
IV. SCREEN SHOTS



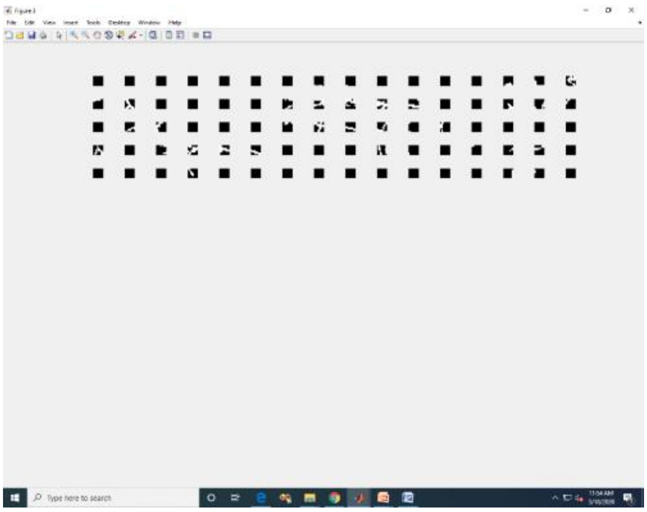
Input Image



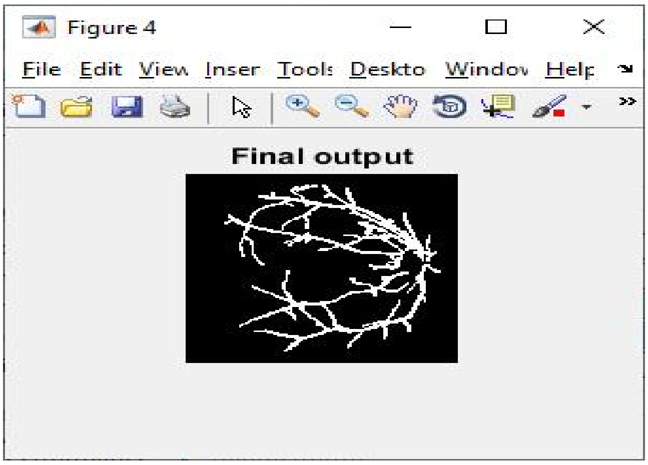
Segmentation



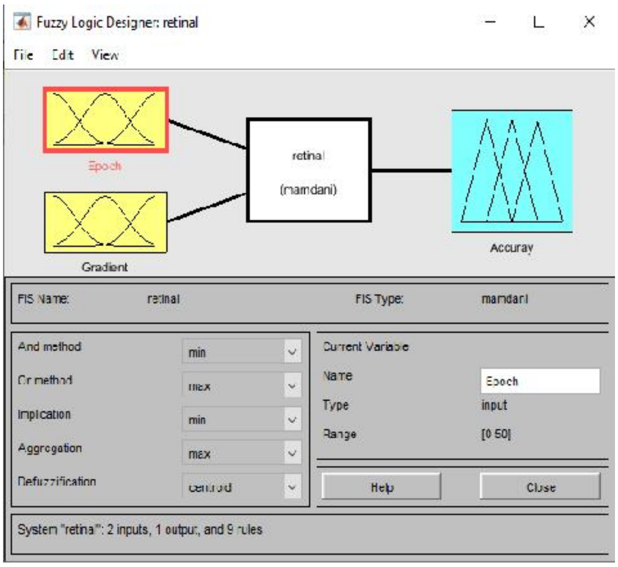
Artificial Neural Network



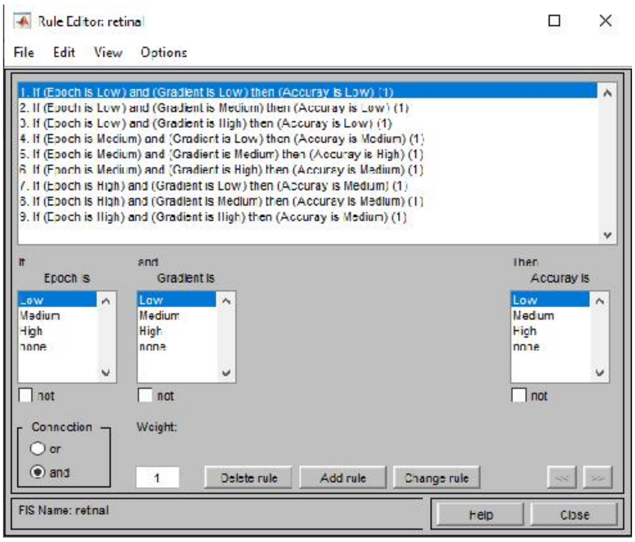
Encoder Image



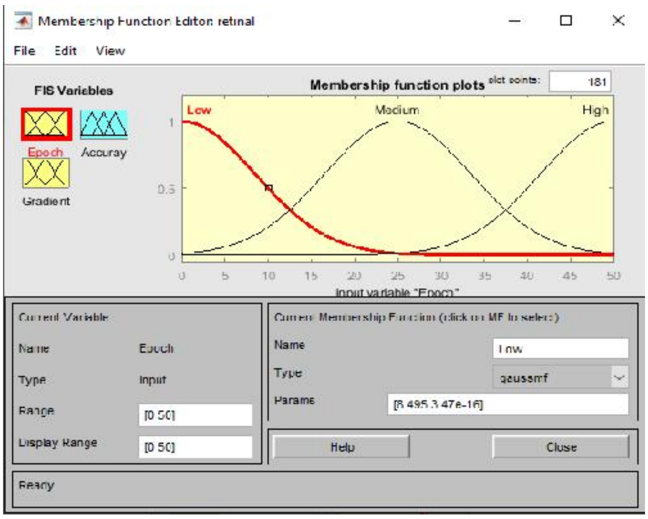
Final Output



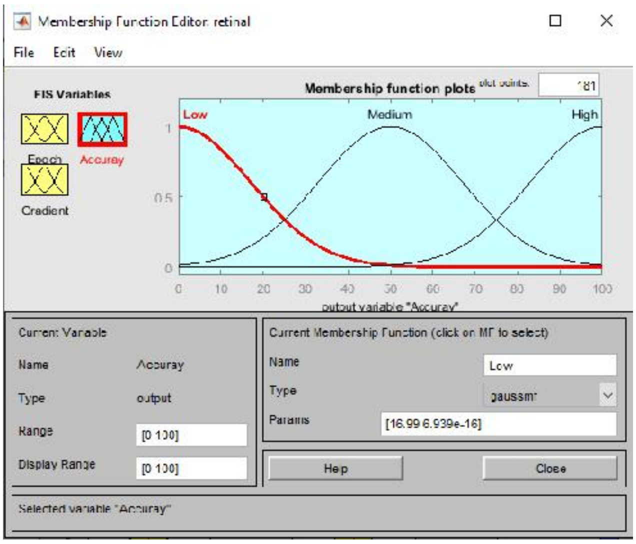
Fuzzy Neural Network (mamdani)



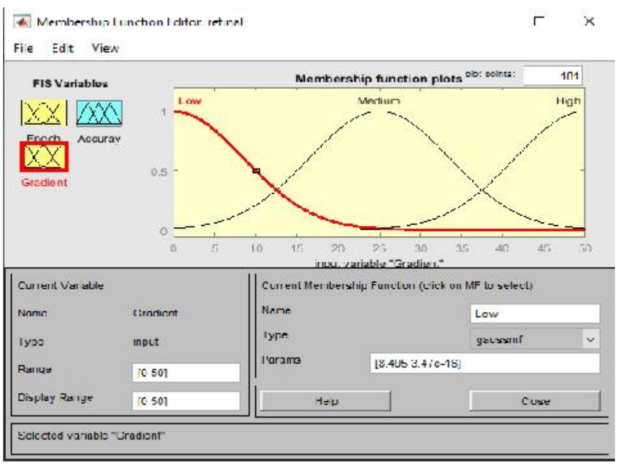
Fuzzy Rules



Membership function of epoch



Membership function of accuracy



Membership function of Gradient

V. CONCLUSION

Thus a new supervised approach for vessel segmentation in retinal images. The segmentation task is remolded as a cross-modality data transformation problem. The proposed network can automatically learn the vascular feature in the training procedure. Thereby, no artificially designed features are needed in the segmentation, reducing the impact of subjective factors. Furthermore, the proposed network is wide and deep and has more a powerful ability for induction than general neural networks have. The proposal is divided into two phases: the training phase and the extraction or processing related to type of image. In this paper these two parts of the network one is neural network for training, second is fuzzy inference system which helps us improve the performance result in face recognition. Fuzzy logic has proved to be a tool that can improve the performance of the existing system.

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