Medical Decision-Making System of Ultrasound Carotid Artery Intima–Media Thickness Using Neural Networks

N. Santhiyakumari · P. Rajendran · M. Madheswaran

Published online: 23 December 2010
© Society for Imaging Informatics in Medicine 2010

Abstract The objective of this work is to develop and implement a medical decision-making system for an automated diagnosis and classification of ultrasound carotid artery images. The proposed method categorizes the subjects into normal, cerebrovascular, and cardiovascular diseases. Two contours are extracted for each and every preprocessed ultrasound carotid artery image. Two types of contour extraction techniques and multilayer back propagation network (MBPN) system have been developed for classifying carotid artery categories. The results obtained show that MBPN system provides higher classification efficiency, with minimum training and testing time. The outputs of decision support system are validated with medical expert to measure the actual efficiency. MBPN system with contour extraction algorithms and preprocessing scheme helps in developing medical decision-making system for ultrasound carotid artery images. It can be used as secondary observer in clinical decision making.

Keywords US carotid artery image analysis · Contour extraction · Multilayer back propagation network · Neural network classifier · Carotid artery classification · Medical decision-making system · Digital image processing · Image segmentation · Decision support techniques · Neural networks · Carotid artery

Background

In recent past, advancements in the field of medical imaging have provided powerful non-invasive techniques to probe various pathologies of human body for better diagnosis. The accurate extraction of anatomical structures from the medical images becomes a challenging task for many clinical and research applications. The acquired ultrasound image is expected to have noise components, which cannot be diagnosed with manual interpretations. The recent developments in medical image analysis have motivated advance research for developing a systematic approach for better interpretation.

The basic idea of medical decision-making (MDM) system is to provide a computer-based output for health care professionals and radiologist for diagnosing the subjects. The system can be considered as “second opinion” for improving the medical image interpretation for efficient diagnostic decision-making process [1–5]. In the past century, the technologies have advanced due to the discovery of X-rays, arteriography, magnetic resonance imaging, magnetic resonance angiography, computed tomography (CT), positron emission tomography, single photon emission computed tomography, and ultrasonography.

Successful development of computer-aided diagnosis (CAD) scheme makes the radiologist investigate the nature of the subjects. It helps in analyzing the patient details quantitatively. It is also used to maximize the effect of

N. Santhiyakumari (✉)
Department of ECE, K.S.R. College of Technology,
Tiruchengode 637215, India
e-mail: santhiyarajee@rediffmail.com

P. Rajendran
Department of CSE, K.S.R. College of Technology,
Tiruchengode 637215, India
e-mail: peerajendran@gmail.com

M. Madheswaran
Center for Advanced Research, Department of Electronics
and Communication Engineering,
Muthayammal Engineering College,
Rasipuram 637 408, Tamilnadu, India
e-mail: madheswaran.dr@gmail.com

computer output for future diagnosis of subjects [6]. Various types of CAD schemes have been developed for detection of lesions and characterization of tissue nature in medical imaging. The advancements in medical imaging over the past few decades have enabled the physicians to non-invasively peer inside the human body for the purpose of diagnosis and therapy. With the advent of medical imaging modalities that provide different measures of internal anatomical structure and function, physicians are now able to perform typical clinical tasks such as patient diagnosis and monitoring.

Recently, organs being subject to research for CAD include the kidney, brain, liver, colon, chest, breast, vascular system, and skeletal system [7]. CAD schemes developed in the earlier days include the detection of lung nodule in chest radiographs and the detection of breast lesions on mammograms. Detection of clustered micro calcifications from mammograms using CAD schemes have been ascribed by Nishikawa et al. [8]; whereas in Huo Zhimin et al. [9] work, an automated method were processed to differentiate the malignant tissues from benign masses. In this, parameters pertaining to analysis include extracted features and density of lesions from the identified neighborhood mass regions.

A novel automated method have been developed by Aoyama et al. [10] based on CAD scheme helps in assisting the diagnosis procedure for radiologists to make the difference between benign and malignant. In this technique, database has been maintained for chest radiograph. Nodules were located with the help of radiologist. The resultant filter images from nodules were represented in a polar coordinate system. Analysis of contour lines of gray level distinction based on polar coordinate representation aids in segmenting the nodules automatically. In this, linear discriminant analysis procedures were used to select the clinical parameters namely age, sex, and features. Cluster of features extracted from the analysis have been used as inputs for artificial neural network (ANN). It was mentioned clearly that this method gave better results as compared with manual method.

Ashizawa et al. [11] suggested a new method that aids in distinguishing various interstitial lung diseases using an ANN. This network was designed in such a way that it differentiates among 11 interstitial lung diseases using ten clinical parameters and 16 radiologic findings. It has been reported that ANN can provide differential diagnosis of interstitial lung disease using chest radiography, and these reports were used as second opinion to assist radiologist. Automated detection of lung nodules in low dose CT images for lung cancer scanning was proposed by Arimura et al. [12]. In this technique, majority of background normal structures were suppressed based on a difference image technique. Difference image for each CT slice was obtained using image subtraction technique.

The subtraction process has been carried out from the suppressed image processed with a ring average filter from the nodule enhanced image with a match filter. Multiple gray level thresholding technique has been used to identify the initial nodule candidates. Two rule-based schemes processed on the localized image features were used to remove a number of false negatives in an entire lung region. ANN was trained in that way to remove the remaining false positives. It has been reported that the CAD scheme provides much appreciable sensitivity and assist radiologists in detecting lung cancers even on low dose CT images.

A novel template matching technique based on genetic algorithm was described by Lee et al. [13] using a CAD scheme. It has been used to detect lung nodules in helical X-ray pulmonary CT images. Conventional template matching technique was also employed along with this technique on the wall area of lungs. False positive findings were eliminated using 13 features extracted from the above techniques. In this scheme, approximately 1.1 sectional images have been achieved from the detection rate of about 72% with false positives.

Solid and subsolid pulmonary modules in CT images were automatically detected using model-based CAD system, which was described by McCulloch et al. [14]. In this technique, multiple segmentation algorithms have been used to extract the noteworthy structures in the lungs. Throughout the lungs, probability of various anatomical events has been determined using Bayesian statistical framework model. This CAD algorithm was used to measure the sensitivity improvement between two radiologists with respect to all noncalcified nodules, solid, and subsolid.

Classification of the hepatic lesions from CT images were proposed by Gletsos et al. [15] using a CAD system. This system has two modules namely feature extraction and classification modules. The feature extraction module was used to calculate the average gray level and texture characteristics from the spatial gray level co-occurrence matrices. This CAD system provides much appreciable classification efficiency in identifying different hepatic lesions using classifier module with three sequentially placed feed-forward neural networks. Schmid-Saugeon et al. [16] presented with a CAD system for pigmented skin lesions. It has the solutions for lesion boundary detection and quantification of degree of symmetry. In this technique, dermatologists were used to validate the detected lesions. A six-dimensional feature vector was used to classify the pigmented skin lesions as benign or malignant using symmetry quantification step.

Verikas et al. [17] investigated an automated analysis of vocal cord images for diseases classification using CAD system. In this method, color, texture, and geometrical features were used for obtaining a concise and informative representation of a vocal cord image. Pattern classifier was

used in this system to categorize the images into healthy, diffuse, and nodular classes analyzed data. Yoshida et al. [18] developed a CAD system for CT colonography (CTC). It also provides radiologists with a second opinion in an automated way to detect the locations of suspicious polyps and masses on CTC.

Jerebko et al. [19] detected the colonic polyps in CTC using a CAD technique. In this investigation, neural networks and recursive binary trees were compared based on the classification results to decide the best classifier. A data base was maintained in this work of about 39 polyps from 3 to 25 mm in size. In this technique, 90% sensitivity and 95% specificity with 16 false positives per study were achieved with trained back propagation neural network with one hidden layer.

The review of literatures in the context of CAD explores its wide spread application in medical diagnosis. Each implementation uses different techniques and developed with an aim of identifying or classifying the pathology of interest. This indicates that each CAD implementation is an application dependent. Similarly in the present work, an effort has been taken to realize a MDM system for classifying three categories of carotid artery using ultrasound (US) as imaging modality. The procedure formulated to develop a MDM system is specific and confined for US carotid artery image. The US CCA images may be diagnosed either subjectively or objectively. In subjective diagnosis, physicians based on their knowledge and expertise in the field interprets the content of CCA region and concludes the CCA category. Obviously, such decisions are susceptible to intra- and inter-expert variability, which makes diagnosis fallacious. An alternative may be the objective methods wherein the interpretations are made with assistance of computing procedures that are built on certain mathematical concepts. Such type of diagnosis offers consistent result and does not depend on the intra- and inter-experts' variability.

US imaging finds wide applications in the diagnosis of human vascular system due to its real time, non-invasive, non-radioactive, and inexpensive nature [20, 21]. Besides the qualitative information for visual interpretation, the quantitative information on the ultrasound scans, such as the sizes, edges, and positions of anatomical structures, is also of significant interest for computer-aided diagnosis. However, the automatic analysis of ultrasound images is a difficult task because of the appearance of speckle patterns caused by the de-phased echoes from the scatterers. Analysis of ultrasound images is complex due to the presence of speckle noise [22, 23].

The speckle often obscures and masks diagnostically important features in US images, and hence, speckle reduction is a critical preprocessing step for feature extraction, analysis, and recognition from medical US

imagery measurements. This has initiated the researchers to develop better medical diagnosis modules and reliable decision-making system. MDM system is being concentrated to use image processing concepts and neural network techniques to assist the physicians to take objective decisions during diagnosis. Although the carotid artery-related diseases are extremely common in elderly subjects, these details are not adequately reported in medical image analysis hitherto [24–26].

The solution to develop such an MDM system for identifying the normal and abnormal subjects is in high demand and to be addressed. In view of the above identified problem in human vascular structure, systematic investigations of ultrasound image capturing and post-processing have been proposed in the present investigation.

Implementing such an MDM system provides certain possibilities like (a) implement a MDM system for analyzing and classifying US carotid artery images namely normal, cerebrovascular, and cardiovascular subjects; (b) the realization of MDM system by contour extraction techniques and neural network decision support system is in high demand and so far has not been reported, (c) establishing a quantitative protocol for ultrasound CCA images, (d) make comparative study on images for objective decision making, (e) develop an expert system that automatically recognizes the pathology or normality, (f) implement image retrieval in medical application system, and (g) examine extent of healing or failure under post-therapy observation [27].

The intention of the decision-making system is to provide desired output based on the input it receives at the time of decision making. This depends on the way by which the system has been explored to the environment during the training phase with the assistance of thickness values. In the present study, decision-making system using neural network classifier is developed. Multilayer back propagation network (MBPN) architecture has been designed to classify the CCA category. The performance of the decision-making module is analyzed in terms of classification efficiency, training, and testing time for all the 100 subjects' thickness values as input. The classification results are cross validated with experts to measure the actual efficiency of the system. This leads to realization of MDM system exclusively for US CCA images.

In the present work, an attempt has been made for the first time to implement an MDM system that facilitates automated classification of US carotid artery images of three categories namely normal (NR), cardiovascular diseases (CVD), and cerebrovascular diseases (CeVD). The prime focus of this paper is to realize a MDM system with an intention to help the medical experts as secondary observer to perform unbiased diagnosis on US carotid artery images and to meet few possibilities of MDM system.

Methods

Medical Decision-Making System of US Carotid Images

The MDM system design requires three main areas for its implementation to detect a specific kind of abnormality,

- (a) General processing techniques include
 - Image acquisition and digitization
 - Image quality verification and reacquisition
- (b) Preprocessing algorithms for segmentation of anatomical structures comprise of
 - Normalization and initialization of CCA images
 - Filtering
 - Speckle reduction
- (c) Analysis aimed at solving a particular task or application. This step includes the following
 - Contour extraction
 - Classification by neural network decision support system
 - Applications

The structured procedure to realize a CCA medical diagnosis decision-making system is shown in Fig. 1. The images acquired by using US scanning system are given as input to the devised MDM system.

In general processing, the acquired image is digitized and verified for the prominent visibility of anatomical structures. The image is reacquired until the physician gets convinced with the quality. As general processing is mostly concerned with the acquisition system and physician decision wherein routine procedures are followed, the explanations and discussions are made extensively pertaining to preprocessing techniques and analysis.

Image Data

US Carotid Artery Images

The images used for the analysis are acquired from two types of scanning systems namely,

- (a) Aloka Prosound Alpha-10 (SSD α -10, model no. M00720 Japan) ultrasound scanner with a high resolution and digital beam former with compound technology has been used for the acquisition of the images. The built-in compound pulse wave generator facilitates to optimize the contrast and to obtain an enhanced focus and spatial resolution. A multifrequency linear transducer with a frequency range of 5–10 MHz has been used for recording the arterial

Fig. 1 Proposed MDM system for CCA ultrasound image analysis

movements. The transducer is operated at a frequency of 7.5 MHz to obtain the arterial movements and the movements are recorded using a video recorder.

- (b) Philips HD11XE US machine (model no.—HDI5000 sonoct) with the broadband compact linear array transducer has been used for the data acquisition of the images. High definition sonoct has been used to capture the real time compound by using transmit beam steering techniques. A multifrequency linear transducer with a frequency range of 7–15 MHz has been used for recording the arterial movements. The transducer is operated at a frequency of 12 MHz to obtain the arterial movements, and the movements are recorded using video recorder.

The sonographic evaluation is made based on the distribution of echogenity that reflects tissue characteristics for better echo visualization. The transverse and longitudinal section of carotid artery is taken to include normal and

abnormal subjects as suggested by the experts. This also ensures better visual interpretation of the normal and diseased carotid artery. The exact transducer position (at right angles to adventitia) can be identified using transducer by placing it at different inclined angles. The video is recorded for a period of 10 s for each subject to show the transverse and longitudinal sections of the CCA. The transducer is placed exactly at the starting point of the bifurcation of CCA to obtain a uniform lumen for different subjects. Thus the left end of the image indicates the starting point of bifurcation.

The recorded video is converted into frames employing video decompiler. The processed frames are stored as still images in a computing system for further processing. In total, 100 images with 50 images in each category are obtained from male and female subjects of age 20–70 years for training and 50 images in each category is acquired under the same age group for testing. The carotid images of normal and abnormal are considered for the analysis. The necessary clinical information of the training images are documented. To make the testing process unbiased, these details are veiled for the test images.

Carotid Artery Diseases

Carotid artery disease is a form of disease that affects the vessels leading to the head and brain [28]. Carotid artery disease is caused by the narrowing or blockage of this artery due to plaque build-up. The CCA Diseases are usually categorized as cardiovascular disease like heart attack, myocardial infarction, cerebrovascular disease-like stroke, carotid stenosis, carotid atherosclerosis, plaque, and arteriosclerosis (cerebral atherosclerosis). It is also caused by means of thickening of arterial layers.

Thickening The circulatory system is one of the body systems most affected by age. The walls of the arteries thicken, losing their elasticity, and become stiffer. This causes a decrease in blood flow to vital organs and causes the blood pressure to rise. Genetics and environmental factors combine over time to cause inflammation of the inner layers of the artery and the formation of plaque on the inner lining of the arterial wall. This thickening can be measured using ultrasound and sophisticated edge-detection software to quantify the amount of disease present.

Preprocessing and Contour Extraction for Carotid Artery of US Carotid Artery Image

In order to preserve the carotid artery region from the overall tissue characteristics, the following preprocessing

procedure has been done prior to the contour extraction technique [29].

- Step 1: Identification of the region of interest from the acquired images and is shown in Fig. 2
- Step 2: Intensity normalization using average intensity histogram
- Step 3: Horizontal smooth filtering to remove echo dropouts in US images and it is shown in Fig. 3
- Step 4: Blurring to locate the vessel interfaces

After the preprocessing steps, the arterial layers have been extracted using improved dynamic programming algorithm [30]. The proposed flow diagram is shown in Fig. 4. Boundaries are detected using optimization principle and its sample is shown in Fig. 5. The thickness values of the arterial boundaries have been measured from the extracted contours. It is given in Tables 1 and 2.

In active contour extraction method, the acquired images have been preprocessed using speckle reducing anisotropic diffusion technique [31] from the initialized region [32]. After speckle reduction, the contours have been extracted using energy minimization process [33, 34]. The extracted contours are shown in Fig. 6. The intima–media thickness values for the extracted boundaries are shown in Tables 1 and 2. The thickness values obtained from two contour extraction techniques have been used as input parameters for neural network classifier.

Fig. 2 Pixel intensity vs. depth (i.e., row index), corresponding to a column of a sample image

Fig. 3 **a** View of B-mode common carotid artery sample frame showing longitudinal section and **b** median-filtered image

Neural Network Classifier implementation

Normally, neural network-based solutions are developed in four steps. They are

1. Data transformation, scaling, or normalization
2. Network architecture definition

Fig. 4 Flow diagram of improved dynamic programming algorithm

Fig. 5 **a** Extracted boundary of normal subjects. **b** Extracted boundary of abnormal subjects

3. Learning algorithm
4. Validation step

First Step In this step, large variation in the input data can slow down or even prevent the training of the network. To overcome this potential problem, the data are usually scaled using statistical, min-max, sigmoidal, or principal component transformations [35]. It is also important that absolute input values are scaled to avoid asymptotic issues [36].

Normalization of the Patterns The patterns are normalized so that the values are in the range of 0 to 1 and the computational complexity is reduced. The normalization of the patterns is done by the following Eq. (1)

$$N_i = N_i / N_{\max} \quad (1)$$

where

N_i is the arterial layer thickness value and $N_{\max}$ is the maximum value of the arterial layer thickness.

Table 1 Intima-media thickness of common carotid artery for normal (healthy) subjects

S. no.	Age group (years)	Number of subjects	Male/female	Intima-media thickness $IMT_{\text{mean}} \pm SD$ (mm)	
				IDP method	AC method
1	21–30	19	F	0.48 ± 0.047	0.28 ± 0.05
2	31–40	15	M	0.61 ± 0.018	0.41 ± 0.02
3	41–50	21	F	0.67 ± 0.011	0.47 ± 0.01
4	51–60	19	F	0.74 ± 0.005	0.54 ± 0.01
5	61–70	7	M	0.79 ± 0.016	0.59 ± 0.02

IDP improved dynamic programming, AC active contour extraction method

Table 2 Intima-media thickness of common carotid artery for abnormal subjects

S. no.	Age group (years)	Number of subjects	Name of pathology	Intima-media thickness $IMT_{mean \pm SD}$ (mm)	
				IDP method	AC method
1	35–55	13	Hypertension	1.45 ± 0.05	2.01 ± 0.04
2	35–55	06	Atherosclerosis	2.35 ± 0.50	3.35 ± 0.41

Second Step In this step, the number of hidden layers, the number of neurons in each layer, and the connectivity between the neurons are set. There are three basic layers or levels of data processing units, namely, the input layer, the hidden layer, and the output layer. Each of these layers consists of processing neurons. The number of input neurons and output neurons and the neurons in the hidden layer depend upon the problem being studied. If the number of neurons in the hidden layer is small, the network may not have sufficient degrees of freedom to learn the process correctly. If the number is too high, the training will take a long time and the network may sometimes over-fit the data [37]. Validation set error is often used to determine the optimal number of hidden neurons for a given study.

Third Step In this step, a learning algorithm is used to train the network to respond correctly to a given set of inputs. The training goal is to find parameters that result in the best performance of the network with unfamiliar

data. An ANN is better trained when more input data is available. Through training, it is possible to determine ANN weights. At the beginning of training, the initial value of weights can be assigned randomly or based on experience. In the process, the learning algorithm systematically changes the weights to perform a desired input–output association correctly. Many methods exist for training, and the process of learning is terminated when the difference between the ANN output and the actual output is small. At this stage, the ANN is considered trained.

Selection of Patterns for Training The number of classes, which are based on the classification range of the outputs, is decided. If only one output is considered, the range of classification is simple. If more than one output is considered, a combination criterion has to be considered. The total number of patterns is decided for each class. Out of these patterns, the number of patterns to be used for training the network is decided. The remaining patterns are used for testing the classification performance of the network. The patterns selected for training the network should be such that they represent the entire population of the data. The selection of patterns is done by Eq. (2).

$$E_i^2 = \frac{\sum_{j=1}^{nf} (x_{ij} - \bar{x}_j)^2}{\sigma_i^2} \quad (2)$$

where E_i^2 is the variance of a pattern, nf is the number of features, and

$\sigma_i^2 = \frac{\sum_{j=1}^{nf} (x_{ij} - \bar{x}_j)^2}{L}$, where $\bar{x}_j$ is the mean for each feature and L is the number of patterns. The value of E_i^2 is found for each pattern. Patterns with maximum E_i^2 are chosen from each class for training the network.

Fourth Step At the end, the validation step in which the performance of the trained ANN model is tested through some selected validation set data. Validation can be employed to monitor the network error during training to determine the optimal number of training iterations. It can also be used to find out the optimal number of hidden neurons.

MBPN

The back propagation learning procedure has become the single most popular method to train networks. It has been used to train networks in problem domains including character recognition, speech recognition, sonar detection, and many more. The MBPN architecture consists of a network of nodes organized in layers as shown in Fig. 7(a).

Fig. 6 **a** Common carotid artery hypertension subject sample. **b** IM layer of hypertension subject

A typical MBPN network consists of three or more layers of nodes: an input layer that receives external inputs, one or more hidden layers, and an output layer which generates the classification results. Note that unlike other layers, no computation is involved in the input layer. The principle of the network is that when data are presented at the input layer, the network nodes run calculations in the consecutive layers until an output value is obtained at each of the output nodes. This output will indicate the appropriate class for the input data.

Training

The training process requires a set of examples of proper network behavior that includes network inputs and target outputs. During the training, the weights and biases of the network are adjusted iteratively to optimize the network performance function. The performance function for the networks is mean square error (MSE)—the average squared error between the network output and the target output. There are generally five steps in the training process:

- Step 1 Preprocess data to produce the most efficient training. It is helpful to preprocess the data before training. This means to scale the inputs and targets data to ensure they always fall within a specified range.
- Step 2 Initialize the weight values. Before training a network, the weights and biases must be initialized. In order to avoid the result located in flat area, random weight values are selected.
- Step 3 For input sample, calculate outputs of arbitrary node in both hidden layer and output layer (in forward propagation).
- Step 4 Calculate errors of hidden layer and output layer (in backward propagation).
- Step 5 Adjust weight values according to error function until the minimal error is achieved. After training, the weights are fixed and can be used for practical classification.

MBPN learning process depends on three parameters namely learning coefficient (η), momentum (β), and mean square error ($\delta_{\max}$). Learning coefficient (η) determines the size of the weight changes. Its useful range is between 0.05 and 2 and depends on the problem. Momentum (β) causes the weight changes to be dependent on more than one input pattern. The change is a linear combination of the current gradient and previous gradient. The useful range for this parameter is between 0 and 1. Mean square error ($\delta_{\max}$) is the parameter where the network error dips below a particular error threshold. A threshold of 0.001 squared errors is usually desirable.

Fig. 7 **a** Neural network architecture for CCA classification. **b** Flow chart for back propagation algorithm

MBPN is trained with the derived layer thickness values irrespective of the significant level and correlation between the categories. The network learning parameters, selection of number of hidden layers, and hidden layer neurons are optimized to yield better classification efficiency.

Back Propagation Algorithm

The algorithm is developed considering supervised method for measuring minimum error value and steepest-descent method to examine a global minimum. The flow chart for the algorithm is given in Fig. 7(b).

The number of processing nodes in the input layer has been chosen based on the problem and the number of inputs given. The number of layers and number of nodes in the hidden layers were also decided. Classification nodes in the output layer also depend on the problem. The connections between nodes are initialized with random weights. A pattern from the training set is presented in the input layer of the network, and the error at the output layer is calculated. The error is propagated backwards toward the input layer, and the weights are updated. This procedure is repeated for all the training patterns. At the end of each iteration, test patterns are presented to ANN and the classification performance of ANN is evaluated. Further training of ANN is continued till the desired classification performance is reached.

Steps Involved

Step 1 The input vector $X=(x_1, x_2, \dots, x_i)t$ has been applied to the input units.

Step 2 Forward Propagation

- The weights and thresholds of the network are initialized.
- The inputs and outputs of a pattern are presented to the network.
- The net input values of the j th hidden layer nodes have been calculated using the following Eq. (3)

$$\text{net } j = \sum_{i=1}^N W_{ji} X_i + \theta_j \quad (3)$$

where W_{ji} is the weights applied between input and hidden nodes, X_i is the input vector, and θ_j is the bias term for the hidden nodes.

- The outputs of each node in the j th hidden layer has been calculated using the given Eq. (4)

$$O(\text{hidden layer}) = \frac{1}{1 + \exp(\text{net } j)} \quad (4)$$

$$O_j = \frac{1}{1 + \exp\left(\sum_{i=1}^N W_{ji} X_i + \theta_j\right)}$$

- Its value has been propagated to the k th output layer, and the net input values to each node in the k th output layer is determined using the Eq. (5)

$$\text{net } k = \sum_{j=1}^L W_{kj} O_j + \theta_k \quad (5)$$

where W_{kj} is the weights applied between hidden and output nodes, O_j is the outputs of the hidden layer, and θ_k is the bias term for the hidden nodes.

- The outputs of each node in the output layer has been calculated, and its formulae is depicted in Eq. (6)

$$O(\text{output of a node}) = \frac{1}{1 + \exp(\text{net } k)}$$

$$O_k = \frac{1}{1 + \exp\left(\sum_{j=1}^L W_{kj} O_j + \theta_k\right)} \quad (6)$$

- The error of an output pattern is calculated as $E(p)$

$$\delta(\text{hidden layer}) = E(p) = (1/2) \sum (d(p) - O_j(p))^2 \quad (7)$$

where $d(p)$ is the desired output and $O_j(p)$ is the actual output from the j th node is shown in Eq. (7).

Step 3 Backward Propagation

- The error for the nodes in the output layer is calculated as $\delta(\text{output layer})$, and it is represented in the Eq. (8)

$$\delta(\text{output layer}) = (1/2) \sum (Y(p) - O_k(p))^2 \quad (8)$$

where $Y(p)$ is the target output and $O_k(p)$ is the actual output from the k th output node.

- The weights between output layer and hidden layer are updated and its equation is given by Eq. (9)

$$W(n+1) = W(n) + \eta \delta(\text{output layer}) O(\text{hidden layer}) \quad (9)$$

- The error for the nodes in the hidden layer is calculated

$$\delta(\text{hidden layer}) = O_k(p)(1 - O_k(p)) \sum \delta(\text{output layer})$$

$$W(\text{updated weights between hidden and output layer}) \quad (10)$$

- The weights between hidden and input layer are updated.

$$W(n+1) = W(n) + \eta \delta(\text{hidden layer}) O(\text{input layer}) \quad (11)$$

Equations (10) and (11) represent the updates of hidden and output layer weights.

The Above Steps Completes One Weight Update

Second pattern is presented and the above steps are followed for the second weight update. When all the training patterns are presented, a cycle of iteration or epoch

is completed. The errors of all the training patterns are calculated and displayed on the monitor as the MSE. It is represented by Eq. (12)

$$E(\text{MSE}) = \sum E(p) \quad (12)$$

Results and Discussion

CCA is categorized based on the output of the decision-making system. Consequently, it is sufficient to have one neuron in the output layer. The results obtained by varying the parameters like learning rate, momentum, and threshold value are discussed and presented here.

Learning Rate

The performance of MBPN for various learning rates (η) in the range of 0.1–1.0 with an incremental value of 0.1 is shown in Table 3. The classification efficiency, training, and testing time are measured for each value of “ η .” The training is made with the layer thickness extracted from 50 images in each CCA category, and to test the MBPN, the same image data set is used. The results obtained shows that the training time changes between 1.94 and 1.34 for increase in “ η ” value. For NR images, maximum classification efficiency of 96% is achieved for $\eta=0.6$ and minimum of 68% for $\eta=1$. In case of CeVD images, for the same value of “ η ,” the maximum classification efficiency obtained is 90%, which is lesser than NR, and no change in minimum value is noticed. The classification efficiency varies from 64% to 92% for CVD, with the maximum classification efficiency of 92% that results for $\eta=0.6$. To select the appropriate and optimum value, it can be seen that for $\eta=0.6$ the classification efficiency is maximum for all three CCA category. Even though the training time is slightly higher by 0.13 s than the overall

average training time of 1.73 s, as the classification efficiency is better, the “ η ” is fixed at 0.6. The average testing time achieved for $\eta=0.6$ is 0.0130 s.

Momentum

The functioning of MBPN for various values of momentum (β) is given in Table 4. The value is varied between 0.001 and 0.01 in steps of 0.001. The classification efficiency, training, and testing times are measured for each value of “ β .” Here also the training is made separately with layer thickness values extracted from 50 contour images in each category, and to test the network, same image data set is used. It can be seen from Table 4 that the best training time of 1.80 is achieved for $\beta=0.004$. This provides the classification efficiency of 96% for NR, 90% for CeVD, and 92% for CVD. The average testing time is higher than the few other cases, but it is almost the same as obtained with “ η .” For $\beta=0.006$, though the classification efficiency is the same as before, the time taken by MBPN to get trained is more. In the remaining cases, both training and testing time for classification efficiency is not favorable. Therefore, the optimum value $\beta=0.004$ is assigned in MBPN architecture.

Threshold Value

The ultimate inference regarding the category also depends on the threshold value fixed at the output units. The performance of MBPN for different threshold value settings is studied by incrementing its value by 0.05 from 0.1 to 1.0. The classification efficiency is noted for each setting, and best possible threshold value is assigned. The results obtained shows for the value in the range 0.40–0.88 mm; the NR images are identified correctly with the classification efficiency of 96%. The CeVD and CVD images are also categorized, but with the classification efficiency of 70% and 76%, respectively. For values from 1 to 2.5 mm, CeVD images

Table 3 Training time and classification efficiency for various learning rate (η)

S. no.	Learning rate (η)	Average training time (in seconds)	Average testing time (in seconds)	Classification efficiency (%)		
				NR	CeVD	CVD
1	0.1	1.94	0.0163	79	82	80
2	0.2	1.92	0.0159	78	81	80
3	0.3	1.90	0.0150	78	76	82
4	0.4	1.88	0.0146	82	80	85
5	0.5	1.78	0.0138	89	85	88
6	0.6	1.86	0.0130	96	90	92
7	0.7	1.67	0.0126	82	84	78
8	0.8	1.56	0.0124	75	76	74
9	0.9	1.45	0.0120	70	74	68
10	1.0	1.34	0.0115	68	72	64

Training time is estimated for 50 training images in each CCA category, and the same image data set is used as a test image to evaluate classification efficiency. The activation function LOGSIG at hidden layer and PURELIN at output layer is fixed. Maximum number of iterations required has been found to be 100,000

Table 4 Training time and classification efficiency for various momentum (β)

S. no.	Momentum (β)	Average training time (in seconds)	Average testing time (in seconds)	Classification efficiency (%)		
				NR	CeVD	CVD
1	0.001	1.98	0.0156	82	84	86
2	0.002	1.74	0.0148	86	85	84
3	0.003	1.91	0.0150	80	78	85
4	0.004	1.80	0.0129	96	90	92
5	0.005	1.77	0.0146	89	85	88
6	0.006	2.34	0.0152	96	90	92
7	0.007	1.88	0.0136	82	84	86
8	0.008	2.63	0.0134	78	80	83
9	0.009	1.56	0.0110	81	80	84
10	0.01	1.66	0.0112	78	84	82

Training time is estimated for 50 training images in each CCA category, and the same image data set is used as a test image to evaluate classification efficiency. The activation function LOGSIG for the hidden layer and PURELIN for the output layer is fixed. Maximum number of iterations required has been found to be 100,000

are discriminated with the classification efficiency of 90%, while NR and CVD with 78% and 64%, respectively.

The CVD images are correctly identified for the value >2.5 mm, and the classification efficiency obtained is 92%. For this threshold value, in case of NR and CeVD, the classification efficiency achieved is 64% and 60% based on this study; the threshold value is fixed to make decision on given input image. The input image is determined as NR category if the achieved output value of MBPN is ≤ 1.0 mm.

If the value is ≥ 1.0 and ≤ 2.5 mm, then the decision on input image is made as CeVD. If the value is greater than 2.5 mm, then the input is assessed as CVD category.

Activation Function

Different activation functions are available in the neural networks. In this study, LOGSIG for the hidden layer and PURELIN for the output layer have been chosen. Similar to

Table 5 Training time and classification efficiency for various hidden units

No. of neurons in the hidden layer	Training status	Average training time (in seconds)	Average testing time (in seconds)	Classification efficiency (%)		
				NR	CeVD	CVD
5	Goal not met	—	—	—	—	—
10	Goal not met	—	—	—	—	—
15	Goal not met	—	—	—	—	—
20	Goal not met	—	—	—	—	—
25	Goal not met	—	—	—	—	—
30	Goal not met	—	—	—	—	—
35	Goal met	1.925	0.0195	70	68	70
40	Goal met	1.765	0.0186	74	70	72
45	Goal met	1.542	0.0170	78	72	76
47	Goal met	1.431	0.0165	82	76	84
49	Goal met	1.322	0.0154	85	82	89
50	Goal met	1.285	0.0132	96	90	92
51	Goal met	1.474	0.0121	87	84	86
53	Goal met	1.678	0.0151	80	82	78
55	Goal met	1.846	0.0196	74	80	76

Training time is estimated for 50 training images in each CCA category and same image data set is used as a test image to evaluate classification efficiency. Mean square error=0.001. Maximum number of iterations required has been found to be 100,000

Table 6 Details of MBPN architecture parameters fixed for MBPN-ANN

S. no.	MBPN architectural issues	Selected design factors
1	Learning rate (η)	0.6
2	Momentum (β)	0.004
3	Threshold value (T_h)	MBPN-ANN: ≤ 1 mm for NR; >1 and ≤ 2.5 mm for CeVD; >2.5 mm for CVD
4	Activation function	LOGSIG at the hidden layer and PURELIN at the output layer
5	Hidden layer	1
6	Number of hidden units	50
7	Input neurons	50
8	Output neurons	1
9	Mean square error (δ)	0.001
10	Number of iterations	100,000

the procedure followed for fixing η , β , and T_h , the training is made with the layer thickness values extracted from 50 contour images in each category and same image data set is used to test the performance of the network.

Hidden Layer

As mentioned, the choice of number of hidden layer and the number of hidden nodes per layer is arbitrary. But to have a systematic approach, one hidden layer is selected initially with one node and increased by one upon estimating training, testing, and classification efficiency. During this process, if the classification efficiency drops or training or testing times increase by increasing the number nodes per layer or the hidden layer, no further modification is made.

The Table 5 shows the results obtained in terms of classification efficiency, training, and testing time. The performance goal of the network which is quantified with the parameter mean square error is assigned as 0.001. For the hidden nodes up to 30, the performance goal is not met. Even though it is possible to achieve the goal for the number of hidden units of 35 to 55, maximum classification efficiency and minimum training and testing times are not achieved

unless the number of hidden nodes is 50. Therefore, for present application, it has been decided to fix the number of hidden layer as one and number of hidden units in that layer as 50.

Table 6 gives the entire details of MBPN parameters, which are selected based on the above results. It is used for implementing the MDM system. Such settings offer the classification efficiency of 96%, 90%, and 92% for NR, CeVD, and CVD, respectively.

Performance of Decision-Making System

The initial requirements to design MBPN are fulfilled by making meticulous study on architectural issues of the network. The appropriate factors are designed and formulated accordingly. Now, with the available decision-making system, the input images of unknown category have to be identified. Reliable and proficient MDM system has been realized based on the classification efficiencies of US CCA images.

Input training patterns for various age groups are decided in this study. Fifty inputs are taken for training the network, and the remaining inputs are taken as test patterns. The output displayed by the test network is “Normal subject” if the layer thickness values are less than 1 mm. If the thickness is more due to the pathologies developed or the thickness is more due to the abnormalities of the vessel, then the output displayed as “Abnormal subject,” such subject has to *meet the physicians* for further diagnosis and treatment. Thus, this study has recorded the outputs obtained for both the normal and abnormal subjects.

Medical Expert Validation

The classification efficiency used to measure the system performance is sufficient to conclude the system functioning in categorizing the input ultrasound CCA images. The output efficiency of MBPN has to be validated for its accuracy in providing the correct information category. This has been done in consultation with the medical expert. The resultant decision on category is validated with the expert, and based on the interpretation of the expert, the actual efficiency is estimated.

Table 7 Medical expert validation of MBPN-ANN classification efficiency

Features	System efficiency (MBPN system)			Actual efficiency (ultrasound system)		
	NR	CeVD	CVD	NR	CeVD	CVD
Age groups						
21–30	78.64	75.26	77.12	72.04	74.78	75.46
31–40	66.46	62.31	64.63	60.25	60.10	61.12
41–50	88.62	84.42	86.62	78.32	76.40	77.73
51–60	74.82	70.72	73.72	70.62	69.92	71.24
61–70	82.43	75.68	77.86	76.86	74.43	75.56

Table 7 provides the system and actual efficiencies of MBPN. When actual efficiency in general, irrespective of the CCA category, is compared with the system efficiency, it can be observed that the actual efficiency is less than the system efficiency expected in very few cases where they are the same. With this result, it should not be interpreted that systems decision on category is always inferior to the medical experts. Based on the domain knowledge, physiological comfort, and surrounding environment, the decision may vary within intra- and inter-experts group. However, the actual efficiency is biased; it can be used to study the decision-making systems performance in comparison with the medical experts diagnosing method.

Conclusion

A neural network-based MDM system for classifying the US carotid artery images of three carotid categories has been developed and implemented. Using suitable preprocessing procedure, pixels of carotid artery regions are retained, which facilitate to extract the contours of the arterial layers. The study reveals that the MBPN-based MDM system developed offers higher classification and actual efficiency. It is described in performance evaluation measure. As the input images are quantified by numerical value, it is possible to create a universal reference for all three categories, make comparative study on values obtained to decide on category, and know the extent of pathology involved. It is also believed that the proposed MDM system may assist the physicians to predict future possibility of normal subject becoming abnormal based on intima-media thickness value. Such an MDM system helps the physician to study extensively the characteristics of carotid artery more reliably, which finds broad clinical application.

Acknowledgments The authors would like to express their gratitude to Dr. S. Suresh, Mediscan systems, Chennai for providing the necessary images for this study.

References

1. Troccaz J, Baumann M, Berkelman P, Cinquin P, Daanen V, Leroy A, Marchal M, Payan Y, Promayon E, Voros S, Bart S, Bolla M, Chartier- Kastler E, Descotes J-L, Dusserre A, Giraud J-Y, Long J-A, Moalic R, Mozer P: Medical image computing and computer-aided medical interventions applied to soft tissues: Work in progress in urology. *Proc IEEE* 94(9):1665–1677, 2006
2. Summers RM: Road maps for advancement of radiologic computer-aided detection in the 21st century. *Radiology* 229:11–13, 2003
3. Maryellen L, Giger NK, Armato SG: Computer-aided diagnosis in medical imaging. *IEEE Trans Med Imag* 20(12):1205–1208, 2001
4. Doi K: Current status and future potential of computer-aided diagnosis in medical imaging. *Br J Radiol* 78:S3–S19, 2005
5. Erickson BJ, Bartholmai B: Computer-aided detection and diagnosis at the start of the third millennium. *J Digit Imaging* 15:59–68, 2002
6. Lodwick GS, Haun CL, Smith WE, et al: Computer diagnosis of primary bone tumor. *Radiology* 80:273–275, 1963
7. Bommanna Raja K, Madheswaran M, Thyagarajah K: A Hybrid Fuzzy-Neural system for Computer-Aided Diagnosis of Ultrasound Kidney Images Using Prominent Features. *J Med Syst* 32:65–83, 2008
8. Nishikawa RM, Giger ML, Doi K, Vyborny CJ, Schmidt A: Computer-aided detection of clustered microcalcifications on digital mammograms. *Med Biol Eng Comput* 33:174–178, 1995
9. Huo Z, Giger ML, Vyborny CJ, Wolverton DE, Schmidt A, Doi K: Automated computerized classification of malignant and benign mass lesions on digitized mammograms. *Acad Radiol* 15:155–168, 1998
10. Aoyama M, Li Q, Katsuragawa S, MacMahon H, Doi K: Automated computerized scheme for distinction between benign and malignant solitary pulmonary nodules on chest images. *Med Phys* 29(5):701–708, 2002
11. Arimura H, Katsuragawa S, Suzuki K, Li F, Shiraishi J, Sone S, Doi K: Computerized scheme for automated detection of lung nodules in low-dose computed tomography images for lung cancer screening. *Acad Radiol* 11(6):617–629, 2004
12. Ashizawa K, MacMahon H, Ishida T, Nakamura K, Vyborny C, Katsuragawa J, Doi K: Effect of an artificial neural network on radiologists' performance in the differential diagnosis of interstitial lung disease using chest radiographs. *Am J Roentgenol* 172:1311–1315, 1999
13. Lee Y, Hara T, Fujita H, Itoh S, Ishigaki T: Automated detection of pulmonary nodules in helical CT images based on an improved template-matching technique. *IEEE Trans Med Imag* 20(7):595–604, 2001
14. McCulloch CC, Kaucic RA, Mendonça PRS, Walter DJ, Avila RS: Model-based detection of lung nodules in computed tomography exams: thoracic computer-aided diagnosis. *Acad Radiol* 11(3):258–266, 2004
15. Gletsos M, Mougiakakou SG, Matsopoulos GK, Nikita KS, Nikita AS, Kelekis D: A computer-aided diagnostic system to characterize CT focal liver lesions: design and optimization of a neural network classifier. *IEEE Trans Inf Technol Biomed* 7(3):153–162, 2003
16. Schmid-Saugeon P, Guillod J, Thiran J-P: Towards a computer-aided diagnosis system for pigmented skin lesions. *Comput Med Imaging Graph* 27:65–78, 2003
17. Verikas A, Gelzinis A, Bacauskiene M, Uloza V: Towards a computer aided diagnosis system for vocal cord diseases. *Artif Intell Med* 36:71–84, 2006
18. Yoshida H, Dachman AH: CAD techniques, challenges and controversies in CT colonography. *J Abdom Imaging* 30:24–39, 2005
19. Jerebko AK, Summers RM, Malley JD, Franaszek M, Johnson CD: Computer-assisted detection of colonic polyps with CT colonography using neural networks and binary classification trees. *Med Phys* 30:52–60, 2003
20. Jegelevicius D, Lukosevicius A: Ultrasonic measurements of human carotid artery wall intima-media Thickness. *Ultragaras* 43:43–47, 2002
21. Touboul P-J: Clinical impact of intima media measurement. *Eur J Ultrasound* 16:105–113, 2002
22. Huang S-F, Chang R-F, Chen D-R, Moon WK: Characterization of speculation on ultrasound lesions. *IEEE Trans Med Imag* 23(1):111–121, 2004
23. Loizou CP, Christodoulou C, Pattischis CS, et al: Speckle reduction in ultrasound images of atherosclerotic carotid plaque. *IEEE Proc. Santorini, Greece: 14th Intl. Conf. Digital Signal Processing*, 2002, 1:525–528

24. Veller MG, Fisher CM, Nicolaides AN: Measurement of the ultrasonic intima-media complex thickness in normal subjects. *J Vasc Surg* 17:719–725, 1993
25. Bottalico MA, Starita A, EcoStudio: A Computer tool to support carotid ultrasound images analysis. *IEEE Engineering in Medicine and Biology* 2428–2430, 2000
26. Morawski AM, Winter PM, Caruthers SD, et al: A semi-automated algorithm for quantification of vessel wall angiogenesis associated with early atherosclerosis using magnetic resonance imaging. *Proceedings of the 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society* 1: 743–746, 2002
27. Santhiyakumari N, Madheswaran M: Medical decision making system using intima media thickness measurement. *Proceedings of Fifth International Conference on Medical Informatics and Telemedicine Conference*, 2008, pp 1
28. Sobieszczyk P, Beckman J: Carotid artery disease. *Circulation* 114:244–247, 2006
29. Santhiyakumari N, Madheswaran M: Estimation of layer thickness of arterio carotis using Dynamic Programming Procedure. *Proceedings of third Cairo International Biomedical Engineering Conference*, 2006, IP2–4. pp 1–4
30. Santhiyakumari N, Madheswaran M: Non-Invasive Evaluation of carotid artery wall thickness using improved dynamic programming technique. *Journal of Signal, Image and Video processing (Springer)* 2:183–193, 2008
31. Santhiyakumari N, Madheswaran M.: Extraction of Intima-Media Layer of Arteria- Carotis and Evaluation of its thickness using Active contour approach. *Proceedings of International Conference on intelligent and advanced systems. IP_MS1.* 582–586, 2007
32. Santhiyakumari N, Madheswaran M: Analysis of Atherosclerosis for identification of Cerebrovascular and Cardiovascular Diseases using Active Contour Segmentation of Carotid Artery. *Proceedings of International Symposium on Global Trends in Bio Medical Informatics Research, Education and Commercialization.* 1. 40, 2008.
33. Santhiyakumari N, Madheswaran M: Analysis of atherosclerosis for identification of cerebrovascular and cardiovascular diseases using active contour segmentation of carotid artery. *International Journal of Biomedical Engineering and Consumer Health Informatics* 1(2):121–125, 2009
34. Santhiyakumari N, Madheswaran M: Detection of the intima and media layer thickness of ultrasound common carotid artery image using efficient active contour segmentation technique. *Journal of Medical & Biological Engineering & Computing (Springer).* MBEC2042, 2011 (under review)
35. Priddy LK, Keller EP: Artificial neural networks an Introduction. SPIE Press. Bellingham. Washington, 2005
36. Haykin S: Neural networks. Macmillan College Publishing Company. Englewood Cliffs, NJ, 1994
37. Karunanithi N, Grenney WJ, Whitley D, Bovee K: Neural Networks for River Flow Prediction. *J Comput Civ Eng ASCE* 8(2):201–220, 1994