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# Accurate Classification of Plaque in Carotid Arteries with Ultra Sound Images

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## Abstract

Detection of carotid atherosclerosis into symptomatic or asymptomatic in cardiac health is analysed using computer aided diagnosis tool. This paper tells the carotid atherosclerosis of patients as symptomatic or asymptomatic. The process involves four steps 1. Pre-processing 2. Feature extraction using discrete wavelet transform 3. Feature selection and classification. The classification is done with SVM classifier and feed forward neural network. The system is evaluated with 93 symptomatic and asymptomatic images. Under this 47 were with symptomatic plaque regions and 46 were asymptomatic plaque regions. We observed that feed forward neural network produces better accuracy with 94% whereas SVM classifier produces 83%.

**Keywords**— feed forward neural network, (SVM) support vector machines, discrete wavelet transform, and carotid atherosclerosis.

## I. INTRODUCTION

Stroke and heart attack are among the most deadly disease in the world. Cardio vascular diseases (CVD) are number one cause of death globally. An estimated 17. 5 million people die every year due to CVD. Among these deaths 7. 4 million die due to coronary heart disease and 6. 7 million were due to stroke. In low and middle income countries over three quarters of death takes place. Out of the 16 million deaths under the age of 70 due to non-communicable diseases, 82% are in low and middle income countries and 37% are caused by CVDs. Stroke is caused due to disruptions of blood flow to heart this results in blockage of oxygen supply to brain which results in death of brain cells and heart attack is caused by blockage of blood flow to heart[2], [3], [4]. Both stroke and heart attack were due to atherosclerosis and high blood pressure. Deposition of plaque thickens the arteries and this results in atherosclerosis. The

thickening of carotid arteries is the strongest predictor of death in world population.
Treatment can be done with proper diagnosis of plaque at correct time. Surgical removal of plaque can reduce the risk of stroke and heart attack[6], [8]. In this paper the ultrasonographic image is processed with image processing were the ultra sound image's features were extracted, selected and classified using SVM classifier and feed forward neural network.
The flow of this paper in section II involves(a) pre-processing (b) feature extraction using discrete wavelet transform (DWT) and feature selection (c) Classification using feed forward neural network and (d) classification using SVM classifier. In section III classification results are presented and this paper concludes in section IV.

## II. CLASSIFICATION SYSTEMS

The proposed system's block diagram is shown in the figure 1. The carotid plaque ultrasound input image is pre-processed, its features are extracted, selected and classified using SVM classifier and feed forward neural network. These systems are briefly explained below.

### A. Pre-processing

The system is evaluated with 93 symptomatic and asymptomatic images. Under this 47 were with symptomatic plaque regions and 46 were asymptomatic plaque regions. With these ultrasound images symptomatic and asymptomatic database were created. Ultra sound imaging is the one of the most popular imaging technic to map the human body. In ultra sound imaging the sound passes through human body and bounces back an echo which consists of information about patent body as image. This image consist of information about patient body organs for diagnoses the disease.
Region of interest (ROI) is selected to remove unwanted portions in the image in pre-processing. The pre-processed image contains less than 25% of original image which will be useful for classification.

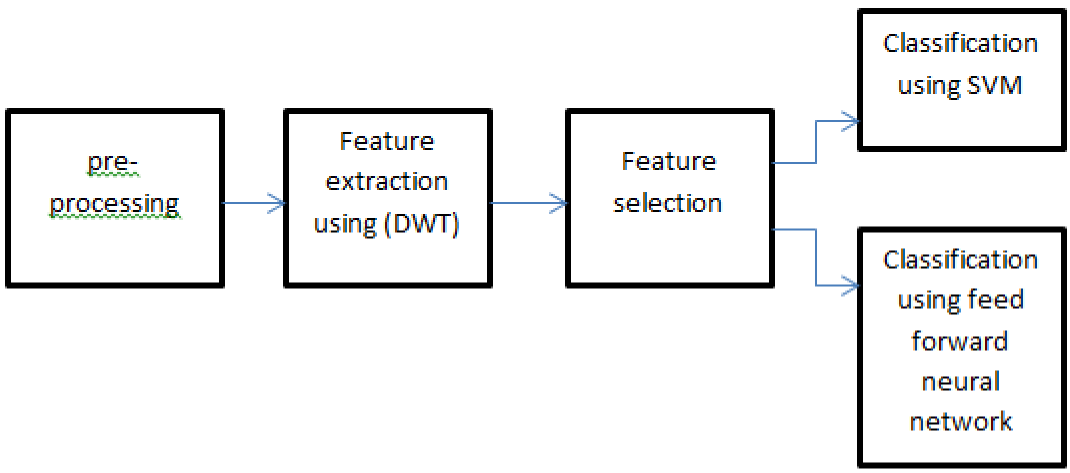
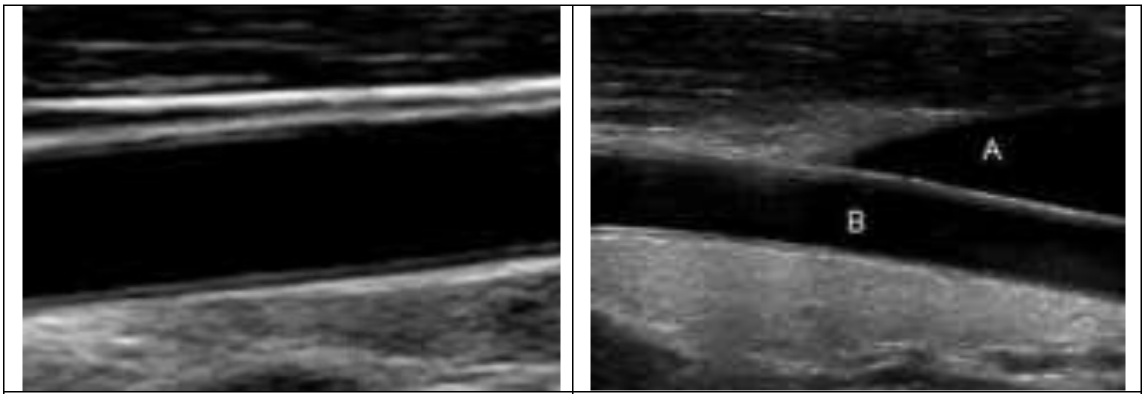
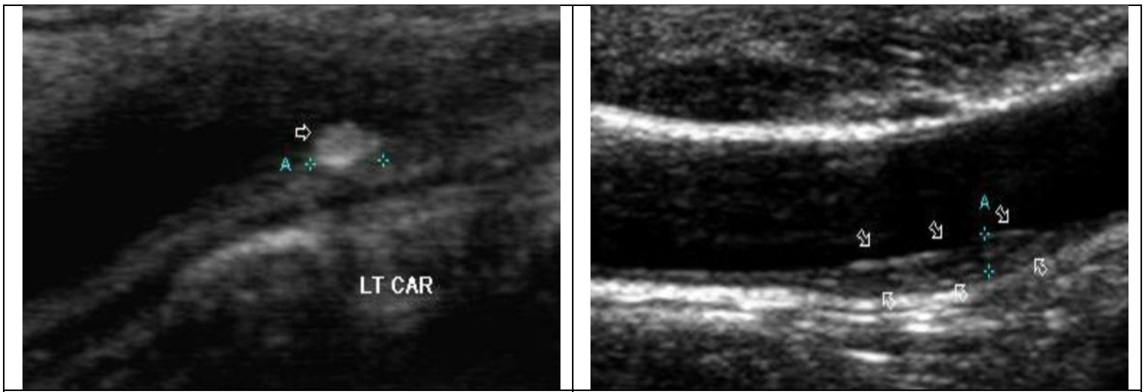



**Figure 1** Block diagram of classification systems




(a) (b)

**Figure 2** ROI selected asymptomtic image




(a) (b)

**Figure 3** ROI selected symptomatic image

### B. Feature extraction using DWT

Feature extraction is done on the ROI selected image to extract the features for classification. feature extraction is done using 2D-DWT and average algorithms. Feature extraction is the form of dimensionality reduction in image processing. If an input to an algorithm is too large to process dimensionality reduction is achieved. Features of the image are extracted in feature extraction andit is applied to the classifier. The extracted features are properly selected with relevant information with reduced representation of input data[5]. The detail and approximation coefficients are calculated using the equations (1) and (2).

$$Ho=\sum_{i=-\infty}^{\infty} x(i)\; h(2n-i) \qquad (1)$$

$$Go=\sum_{i=-\infty}^{\infty} x(i)\; g(2n-i) \qquad (2)$$

2D-DWT uses several filters, among those filters biorthognal3. 1(bior3. 1) filter produces better results hence bior3. 1 family is used for feature extraction. The DWT of the signal is obtained by sending the signal to sequence of down sampling low and high pass filter. The high pass filter output detailed coefficient and low pass filter output is approximation coefficient.

To get redundant sample value these high-pass and low-pass filter outputs are down sampled which have high information content. Bandwidth and frequency resolution gets doubled with this operation. The down sampled output of high-pass and low-pass filter is filtered with sets of low-passand high-pass filters for columns. 2D-DWT of first level produces four matrices values namely Dh1, Dv1, Dd1 and A1. 2D-DWT second level produces four matrices in each of the obtained matrices such as Dh2, Dv2, Dd2 and A2. DWT decomposition is shown in the figure 4. Numbers of elements of these matrices are too high because the matrices are intensity values which cannot be classifiedbytheclassifier directly. Therefore we use two averaging methods and energy for SVM classification and two averaging methods energy, entropy, standard deviation and covariance for feed forward neural network. Equation 3, 4, 5, 6, 7 and 8 shows the two averaging methods, energy, entropy, standard deviation and co-variance.

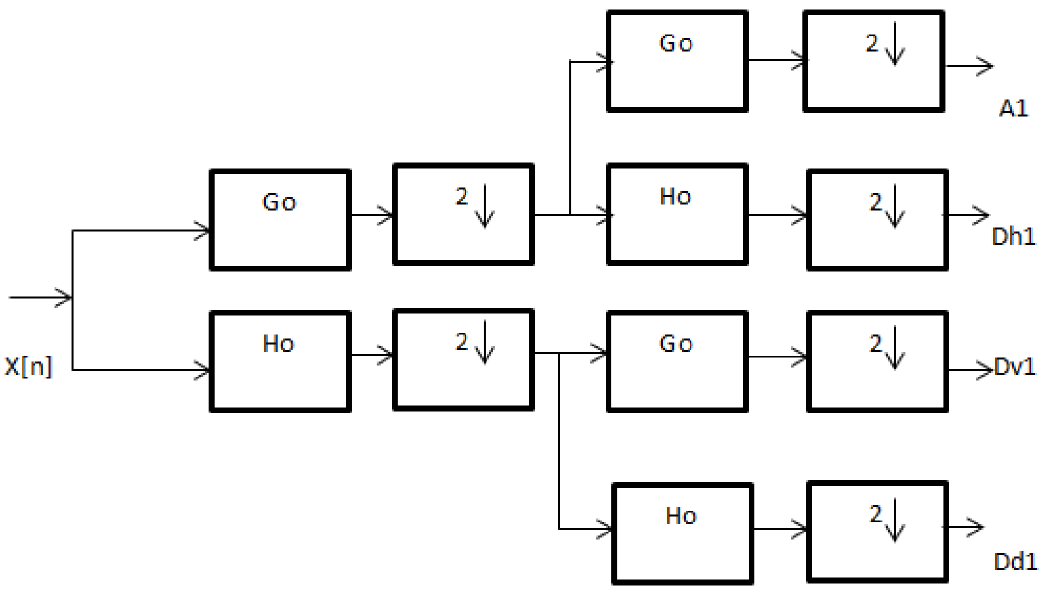



**Figure 4** Wavelet decomposition

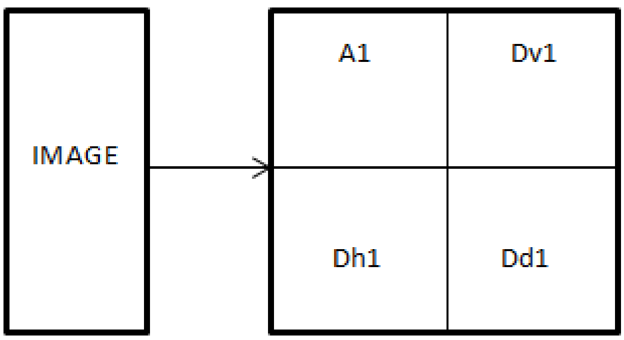



**Figure 5** Image decomposition

Avg Dh1= (1/L×M)
$\sum_{x=(L)}$ | Dh1 x, y | $\sum_{y=(M)}$ | Dh1 x, y | (3)
Avg Dv1= (1/L×M)
$\sum_{x=(L)}$ | Dv1 x, y | $\sum_{y=(M)}$ | Dv1 x, y | (4)
Energy(E)=(1/L²×M) $\sum_{x=(L)}( \text{Dv1}( x, y) )^2 \sum_{y=(M)}( \text{Dv1} (x, y ))^2$
Entropy H(X) = $-\sum_{i=1}^{n} Pi \log Pi$ (6)
Standard deviation = $\frac{1}{N-1}\sum_{i=0}^{N-1}(xi-\mu)^2$ (7)
Co-variance = E ((Xi-µi)(Xj-µj)) (8)

**Table I:** Symptomatic versus asymptomatic features obtained using DWT Bior3. 1

| Features | symptomatic | asymptomatic |
|---|---|---|
| Avg 1 | 0. 0727 | 0. 1427 |
| Avg 2 | 0. 1411 | -0. 4069 |
| Energy | 0. 0051 | 0. 0045 |
| Entropy | 0 | 0. 6122 |
| Standard deviation | 28. 4137 | 16. 7915 |
| Covariance | 77. 8681 | 463. 9742 |

### *C. Feed Forward Neural Network*

Artificial neural networks are very popular imageprocessing and data mining tool. The artificial neural networks are modelled to function like human brain with which we can model any algorithm that can be run efficiently on computers. Human function is controlled by biological neurons inside the human brain, similarly artificial neurons sends activation functions between each layers and nodes which functions the neural network algorithm. Therefore neural networks can be useful forseveral applications such as clustering, classification, function approximation, time series prediction, anddescriptivemodelling. In this paperfeed forward neural network is used for classification. Data in feed forward neural network willmove only in forward direction, from input neurons hidden neuronand output neurons. activation function is activated to activate each neurons [16]. The equation (6)and (7) shows the input and output activation functions. Input is given in the input layer, classification is done in the hidden layer and output is taken from output layer. Activation signals are sent from one neuron to other neurons called weights. The activation signals can be sent to correct neurons with source and destination address inside the weight. The weights are given by Wi, jwhere i isthe source and j is the destination.

a(X)= b+Σiwixi (6)
h(X)= g(a(X)) (7)

In the classification the symptomatic plaque is given a value of 1 and asymptomatic plaque is given a value of 0. The feed forward neural network classifies the symptomatic and asymptomatic plaque by separating 0’s and 1’s values with high accuracy and it has also designed to detect the condition weather the affected plaque is normal or abnormal and blood clot. Three sets of images are used in this paper.

Two sets of symptomatic and asymptomatic images are used for training and one set of symptomatic and asymptomatic images is used for testing.

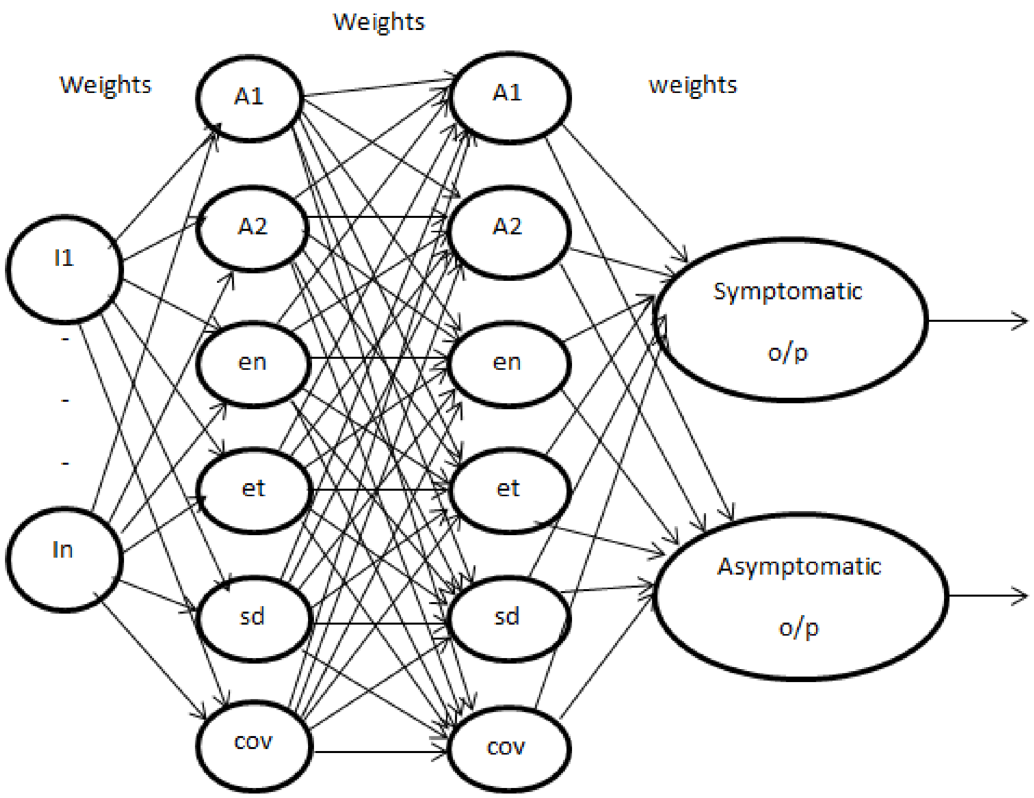



**Figure 5** Feed forward neural network

D. ***SVM CLASSIFIER***

A non- parametric classifier classifies the data with a hyperplane. One such classifier is SVM classifier. Set of objects that has different classes can be separated using hyperplane. When classifying plaque the symptomatic class assumes the value '1' and asymptomatic case assumes the value '0'. With these conditions, a SVM classifier can classify symptomatic and asymptomatic cases with high accuracy. Hyperplane is given by

$f(x)=G_0+G^Tx$

Where $G_0$ is bias and G is a constant for weight vector. Scaling$G_0$ and $G^Tx$, hyperplane can be represented as infinite number. One representation of the hyperplane can be chosen from many and it is given by

$|G_0+G^Tx|=1$

The Training examples which are vicinity to the hyperplane may be represented using x. The distance between a point x and a hyperplane $G_0$ and $G^T$shall be derived from the result of geometry.

Distance= $\frac{|G_0+G^T\text{x}|}{||G||}$

For canonical hyperplane, the numerator is one and the distance to the support vectors is

Distance $_{\text{support vector}}$= $\frac{|G_0+G^T\text{x}|}{||G||}=\frac{1}{||G||}$

M=$\frac{2}{||G||}$

where M represents margin and it is twice the distance to the closest examples. Finally, M can be maximized minimizing a function L(G) subject to some constraints. The constraints model is $x_i$.

$\text{Min}_{G,\,G0}\ L(G)=\frac{1}{2}||G||^2$ subject to $y_i\ (G^Tx_i+G_0)\geq 1$

Where $y_i$ represents labels of the training examples. It poses some Lagrangian optimization issues that can be solved using Lagrange multipliers to obtain G and the b$G_0$ of the optimal hyperplane

## III. RESULTS

### A. *Significant features*

Feature extraction is done with DWT bior3. 1 wavelet. Features selected such as horizontal coefficient A1, vertical coefficient A2, energy, entropy, standard deviation and co-varianceare classified with feed forward neural network and features such as horizontal coefficient A1, vertical coefficient A2 and energy are fed to the SVM classifier for classification.

### B. *Classification results*

In this paper for feature extraction we compared several wavelet functions. Among that bior3. 1 wavelet performed better than others hence for feature extraction bior3. 1 wavelet is used. Classification is done with SVM classifier and feed forward neural network classifier.

Classification is done with SVM classifier and feed forward neural network. The comparative performance is feed forward neural network produces better result of 94% whereas SVM classifier produces 83%. The performance is calculated by number of true positive (TP), false positive (FP) true negative (TN), and false negative (FN). True positive (TP) is the number of symptomatic samples identified as symptomatic. True negative (TN) is the number of asymptomatic plaques classified as asymptomatic. False negative (FN), is the number of symptomatic samples classified as asymptomatic, and falsepositive (FP) is the number of asymptomatic samples classified as symptomatic.

The symptomatic cases are calculated by the formula TP/ (TP + FN) called as sensitivity. The asymptomatic cases which are calculated by the formula TN/ (TN +FP) called as specificity. The ratio of the number of correctly classified samples to the total number of samples which are calculated by the formula (TP + FP)/ (TP+ FP + TN + FN) called as accuracy. PPV is considered as symptomatic subjects among those whichwerelabelled symptomatic by the technique. NPV is considered as asymptomatic subjects among those which were labelled asymptomatic by the technique. Our result shows that the feed forward neural network offers better result than the SVM classifier with accuracy of 94. 5%, sensitivity of 93. 61% and specificity of 95% for thesymptomatic and asymptomatic plaques classification. The table IIshows the performance calculation.

**Table II:** Performance calculation for symptomatic and asymptomatic plaques using feed forward neural network

| Performance | SVM | FFNW |
|---|---|---|
| Iinputs | 93 | 93 |
| True positive (TP) | 40 | 45 |
| True negative(TN) | 37 | 43 |
| False negative (FN) | 9 | 3 |
| False positive (FP) | 7 | 2 |
| Specificity (%) | 83. 7 | 95 |
| Sensitivity (%) | 82. 4 | 93. 6 |
| Accuracy (%) | 83. 6 | 94. 5 |
| NPV (%) | 82 | 93 |
| PPV (%) | 83. 7 | 95. 6 |

## IV CONCLUSION

Diagnosing plaques and blood clot from ultra sound images are difficult. Only experienced surgeons can diagnose the blood clot, symptomatic and asymptomatic plaques from ultrasound images.

With our present systems reduces some of theDifficulties in diagnosis and classification of plaques and blood clot from ultrasound images. This system can be useful as diagnostic tool in modern clinical practice in detection of carotid plaques. Our systems uses DWT for feature extraction and diagnoses the classes with accuracy, specificity and sensitivity. With thesemethods we obtained highest classification accuracy of 94. 5% with feed forward neural network and 83% with SVM classifier. By comparing feed forward neural network and SVM classifier feed forward neural network produces better results. Therefore we believe the proposed methodscan be an effective technique which serves as a effective tool for the vascular surgeons in patients for treatment of risky stenosis. To improve the accuracy furthermore, our feature work includes in studying more feature extraction and classification methods to improve accuracy.

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