iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 3 **Issue:** VI **Month of publication:** June 2015

DOI:

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

International Journal for Research in Applied Science & Engineering Technology (IJRASET)

An Accurate and Generalised Approach to Plaque Characterisation in Ultrasound Scan of Atherosclerosis Diseases

A. Selvi[1], A. Dinesh Kumar[2], S. Arockya Selphine[3],N. Famitha Banu[4]
[1]*Assistant Professor,* [3]*UG Scholar, Department of Biomedical Engineering*
Dhanalakshmi Srinivasan Engineering College, Perambalur, Tamilnadu, India
[2]*Assistant Professor,Department of Mathematics*
Dhanalakshmi Srinivasan Engineering College, Perambalur, Tamilnadu, India

Abstract--Quantitative characterisation of carotid atherosclerosis and classification into symptomatic or asymptomatic is crucial in planning optimal treatment of athermanous plaque. The computer-aided diagnosis (CAD) system described in this paper can analyse ultrasound (US) images of carotid artery and classify them into symptomatic or asymptomatic. Modern medical ultrasound equipment performs real-time high resolution imaging without the use of ionizing radiation. The cost-effectiveness and portability of this facility are particularly important in small-scale hospitals, in which the equipment is useful in conducting complex medical imaging in a timely manner. The use of ultrasonic images to analyze the homogeneity of an internal echo is important to physicians in making diagnostic decisions. However, medical ultrasound images contain significant speckles, noises and ultrasound examination is operator dependent owing to experiences of the interpreter. A computer-aided diagnosis (CAD) system will provide a second beneficial opinion and avoid inter-observer variation. Hence CAD has become a major research topic in medical ultrasound imaging and diagnosis. The artificial neural networks and support vector machines (SVMs) models are extensively used in classification for its ability to model the complex system. Various Atherosclerosis ultrasound CAD systems using the neural network and SVM algorithms have been proposed and the results demonstrated that the classification models have their potential effectiveness. So that patient at risk of stroke can be identified.

Keywords: Atherosclerosis, carotid ultrasound, classification, discrete wavelet transform (DWT), gray scale features, support vector machine (SVM).

I. INTRODUCTION

The fast development of computer applications came with an enormous increase of the use of digital images, in the domain of multimedia, games, satellite transmissions and medical imagery. In medical imagery its plays a vital role in determination of patient's risk. Atherosclerosis is a disease in which plaque builds up inside arteries. Plaque is made of fat, cholesterol, calcium, and other substances found in the blood. This plaque hardens and narrows your arteries which limit the flow of oxygen-rich blood to organs and other parts of your body. Atherosclerosis can lead to serious problems, including heart attack, stroke, or even death. Atherosclerosis can affect any artery in the body, including arteries in the heart, brain, arms, legs, pelvis, and kidneys. As a result, different diseases may develop based on which arteries are affected.

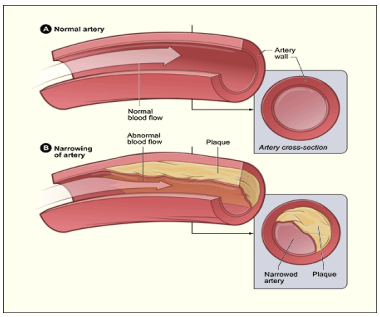


Figure (1): Normal Artery with normal blood flow and Artery with plaques builds ups

Coronary heart disease (CHD), also called coronary artery disease, is the #1 killer of both men and women in the United States. CHD occurs if plaque builds up in the coronary arteries. These arteries supply oxygen-rich blood to your heart. Plaque narrows the coronary arteries and reduces blood flow to your heart muscle. Plaque build up also makes it more likely that blood clots

will form in your arteries. Blood clots can partially or completely block blood flow. If blood flow to your heart muscle is reduced or blocked, you may have angina (chest pain or discomfort) or a heart attack. Plaque also can form in the heart's smallest arteries. This disease is called coronary micro vascular disease (MVD). In coronary MVD, plaque doesn't cause blockages in the arteries as it does in CHD. Carotid artery disease occurs if plaque builds up in the arteries on each side of your neck (the carotid arteries). These arteries supply oxygen-rich blood to your brain. If blood flow to your brain is reduced or blocked, you may have a stroke. Peripheral arterial disease (P.A.D.) occurs if plaque builds up in the major arteries that supply oxygen-rich blood to your legs, arms, and pelvis. If blood flow to these parts of your body is reduced or blocked, you may have numbness, pain, and, sometimes, dangerous infections. Chronic kidney disease s can occur if plaque builds up in the renal arteries. These arteries supply oxygen-rich blood to your kidneys. Over time, chronic kidney disease causes a slow loss of kidney function. The main function of the kidneys is to remove waste and extra water from the body. Atherosclerosis is now a days a growing diseases and its effect on mankind is high and risky. Plaque rupture is often the precipitating event in acute coronary syndromes. Image processing has been used to; diagnose the plaque vulnerability to the efficient treatment. Plaque has been classified into symptomatic and Asymptomatic based on its vulnerability.

The important salient features are extracted from the B-mode ultrasound images using discrete wavelet transform (DWT) and fed to the support vector machine (SVM) classifier for automated classification. The flow of this paper is as follows. Section II briefly describes the following: (A) the data acquisition and pre-processing steps; (B) the method used to extract features using DWT;(C) the statistical t-test technique used to select the suitable features for input to the classifiers; and (D) the SVM classifier and its various kernel functions. Classification results are presented in Section III. The results are discussed in Section IV, and finally, this paper concludes in the Section V.

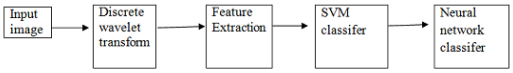


Fig.2. Block Diagram of the Classification system

II. MATERIALS AND METHODS

Figure 2 shows the block diagram of the proposed system. The ultrasound images of carotid plaque are pre-processed and subjected to feature extraction using DWT technique. Subsequently, the significant features are extracted using Student's t-test. Selected features are then fed to the SVM classifier for classification. These techniques are briefly described in this section.

A. Ultrasound Images Of Carotid Plaque

The following prerequisites essential for successful image normalization were carried out: 1) Dynamic range adoption; 2) frame averaging (persistence); 3) time gain compensation curve was sloping through the tissues, and hence, was positioned vertically through the lumen of the vessel because the ultrasound beam was not attenuated when passed through blood, and this ensured that the adventitia of the anterior and posterior walls had similar brightness; 4) gain adjustment; 5) post processing with a linear transfer curve; 6) the ultrasound beam was at 90◦ to the arterial wall; 7) the minimum depth was used so that the plaque occupied a large part of the image; and 8) the probe was adjusted so that adventitia adjacent to the plaque was clearly visible as a hyper echoic band which may be used for normalization. The gray scale images were normalized (using blood and adventitia as reference points) manually by adjusting the image linearly so that the median gray level value of blood was in the range of 0–5 and the median gray level of adventitia (artery wall) was in the range of 180–190. The plaques from patients having retinal or hemispheric symptoms (unstable plaques), such as stroke, transient ischemic attack (TIA), and amaurosisfugax (AF), were grouped as symptomatic plaques (88 stroke, 70 TIA, and 38 AF) 196. Asymptomatic plaques were from patients who had no symptoms in the past. During pre-processing, the region of interest (ROI) was selected by the medical practitioner from each of the studied images prior to feature extraction. The vascular surgeons and sonographers are trained to identify the hypo echoic region representing hard plaque or stenosis. Therefore, we adapted the manually segmented plaque regions in this work. The nature of the disease is focused on the vessel wall that specifically changes the morphology of the lumen–intima interface from slow gradual lipid formation and maturing into hard plaque or loose island of hemorrhage [2]. Thus, the young and old plaques are all focused toward the vessel disease which yields the information in the form of echogenicity in the ultrasound image [6]. Therefore, the focused ROI constitutes less than 25% of the image frame, and hence, the vascular surgeons are keenly interested in the characterization of plaque in this regional information. We are therefore focused in this paper in analyzing the small ROI traced by the vascular surgeon.

Volume 3 Issue VI, June 2015
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

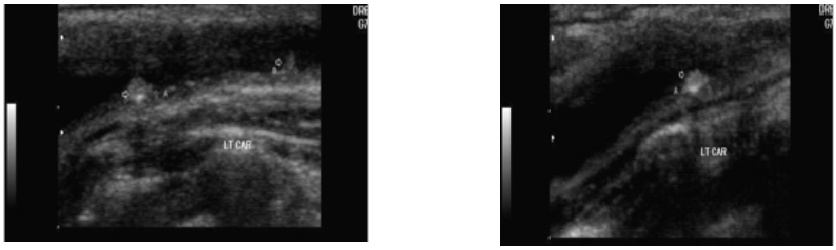


Figure (3): Cartoid images of Asymptomatic (AS) and Symptomatic (AF)

Typical asymptomatic and symptomatic carotid images are shown in Fig. 3 shows the ROIs of the symptomatic and asymptomatic carotid images.

B. Feature Extraction

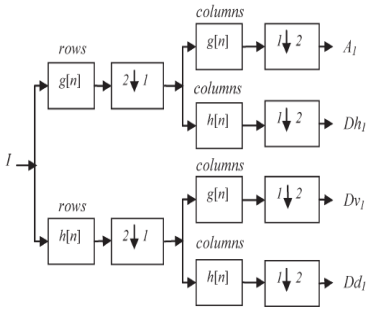
In this paper, we used 2-D DWT and averaging algorithms feature extraction. We start the discussion of these methods by introducing the DWT, which analyzes 1-D signals. Later, we extend the concept to 2-D images. By considering all degrees of freedom that such 2-D signals offer, we arrive at the definition of 2-D DWT. Finally, we define the averaging methods used on The 2-D DWT results which yield the feature vector elements. The DWT transform of a signal x is determined by sending the signal through a sequence of down-sampling high- and Low-pass filters. The low-pass filter is defined by the transfer function g[n], and the high-pass filter is defined by the transfer function h[n]. The output of the high-pass filter D[n] is known as the detail coefficients. The following equation shows how these coefficients are obtained

$$D[n] = \sum_{k=-\infty}^{\infty} x[k]h[2n-k]. \tag{1}$$

The output of the low-pass filter is known as the approximation coefficients. These coefficients are found by using the following equation:

$$A[n] = \sum_{k=-\infty}^{\infty} x[k]g[2n-k]. \tag{2}$$

The frequency resolution is further increased by cascading the two basic filter operations. To be specific, the output of the first-level low-pass filter is fed into the same low- and high-pass filter combination. The detailed coefficients are output at each level, and they form the level coefficients. In general, each level halves the sample number and doubles the frequency resolution. Consequently, in the final level, both detail and approximation coefficients are obtained as level coefficients. For 2-D signals, the 2-D DWT can be used. Our discussion focuses on wavelet packets (WPs) for images. These images are represented as an m × n gray scale matrix I[i, j] where each element of the matrix represents the intensity of one pixel. All
no border pixels in I[i, j], where i_∈ {0,m} and j _∈ {0, n}, have eight immediate neighbouring pixels. These eight neighbours can be used to traverse through the matrix. However, changing the direction with which the matrix is traversed just inverts the sequence of pixels, and the 2-D DWT coefficients are the same. For example, the WP result is the same when the matrix is traversed from left to right as from right to left. Therefore, we are left with four possible directions, which are known as decomposition corresponding to 0◦ (horizontal, Dh), 90◦ (vertical, Dv) and 45◦ or 135◦ (diagonal, Dd) orientations. The implementation of this algorithm follows the block diagram



Volume 3 Issue VI, June 2015
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

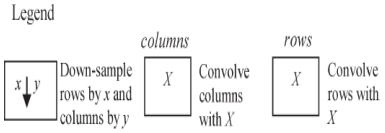


Fig.4. DWT decomposition

shown in Figure (4). The diagram shows the N ×M dimensional input image I[i, j] and the results for level 1. In this paper, we found that the results from level 1 were sufficient to obtain significant features. In this paper, we have evaluated several wavelet functions. Each of these wavelet functions has both a unique low-pass filter transfer function g[n] and a unique high-pass filter transfer function h[n]. Fig. 5 shows the transfer functions for the biorthogonal 3.1 (bior3.1) family used in this work.

The first-level 2-D DWT yields four result matrices, namely, Dh1, Dv1, Dd1, and A1, whose elements are intensity values. Fig. 6 shows a schematic representation of these result matrices. Unfortunately, these matrices cannot be used for classification directly because the number of elements is too high. Therefore, we defined two averaging methods which represent result

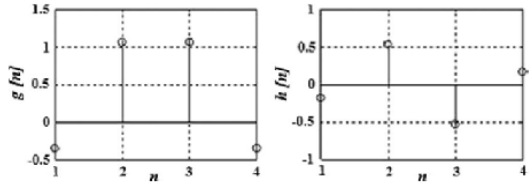


Fig.5. Transfer Functions of the biorthogonal wavelet

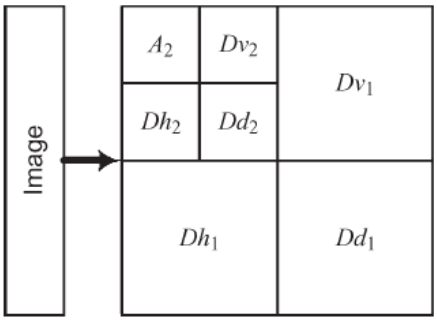


Fig.6. Wavelet based image decomposition

matrices with just one number. The first method is used to extract average measures from 2-D DWT result vectors.

$$Average\ Dh_1(Ah) = \frac{1}{N \times M} \sum_{x=\langle N \rangle} \sum_{y=\langle M \rangle} |Dh_1(x,y)| \quad (3)$$

$$Average\ Dv_1(Av) = \frac{1}{N \times M} \sum_{x=\langle N \rangle} \sum_{y=\langle M \rangle} |Dv_1(x,y)| \quad (4)$$

The final averaging method uses averages not the intensity values as such but the energy of the intensity values

$$Energy(E) = \frac{1}{N^2 \times M^2} \sum_{x=\langle N \rangle} \sum_{y=\langle M \rangle} (Dv_1(x,y))^2 \quad (5)$$

These three elements form the feature vector.

C. Statistical Tests

We have used t-test [8] to verify if the features are significant enough to be able to accurately discriminate the symptomatic and asymptomatic classes. In this test, initially, the null Hypothesis assumed that the means of the feature from the two classes are equal. Then, the t-statistic, which is the ratio of the difference between the means of a feature from two classes to The standard error between class means and the corresponding p-value are calculated. The p-value is the probability of rejecting the null hypothesis given that the null hypothesis is true. In our case, we assumed a normal distribution of the features, but the scaling term in the test statistic was known. Therefore, it was replaced by an estimate based on the data. A low p-value (less than 0.01 or 0.05) indicates that the means are significantly different for the two classes, and hence, the feature is significant.

III. RESULTS

A. Significant Features

The features selected were as follows: energy and average horizontal and vertical DWT coefficients. These features were fed to the SVM classifier for automatic detection of the unknown class. Table I presents the features obtained using DWT with the bior3.1 wavelet. A p-value of less than 0.0001 indicates that the features are significant.

Table.1 Classification results obtained using the dwt features in the various configurations of the svm classifier. A:accuracy. Sn: sensitivity.Sp: specificity

SVM	TN	FN	TP	FP	A (%)	PPV (%)	Sn (%)	Sp (%)
Linear	48	8	37	11	81.7	77	82.2	81.3
Polynomial Order 1	48	8	37	11	81.7	77	82.2	81.3
Polynomial Order 2	51	9	36	8	83.7	81.8	80	86.4
Polynomial Order 3	53	12	33	6	82.6	84.6	73.3	89.8
RBF	50	11	34	9	80.8	79	75.5	84.7

True negative (TN) is the number of asymptomatic plaques identified as asymptomatic. True positive (TP) is the number of symptomatic samples identified as symptomatic. False negative (FN), on the other hand, is the number of symptomatic samples identified as asymptomatic, and false positive (FP) is the number of asymptomatic samples identified as symptomatic. Sensitivity, which is the probability that the technique will identify symptomatic cases, is calculated as TP/(TP + FN), and specificity, which is the probability that the technique will identify asymptomatic cases, is determined as TN/(TN + FP). PPV, which is the proportion of symptomatic subjects among those who were labeled symptomatic by the technique, is calculated as TP/(TP + FP), and accuracy, which is the ratio of the number of correctly classified samples to the total number of samples, is calculated as (TP + FP)/(TP + FP + TN + FN). Our results show that the SVM classifier with the polynomial kernel of order 2 achieved an average accuracy of 83.7%, sensitivity of 80%, specificity of 86.4%, and PPV of 81.8%. In order to select an optimal classifier, one has to choose a classifier which gives equally high values for both sensitivity and specificity. Such equal values indicate that the classifier has good capability in discriminating both the classes without bias toward a particular class. Moreover, the overall accuracy of the classifier should also be high. Based on these criteria, the SVM classifier with a polynomial kernel of order 2 was found to be suitable for this carotid plaque classification problem.

IV. IV.EXPERIMENTAL RESULTS

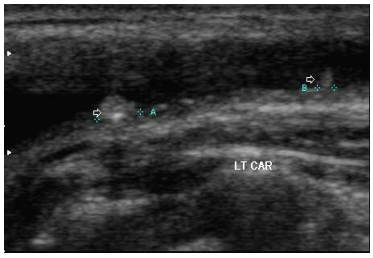


Figure (7): Input

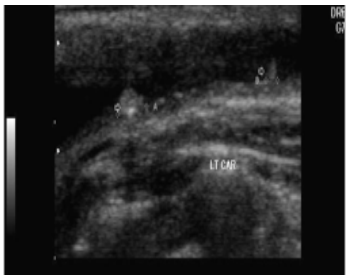


Figure (8): ROI

Volume 3 Issue VI, June 2015
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

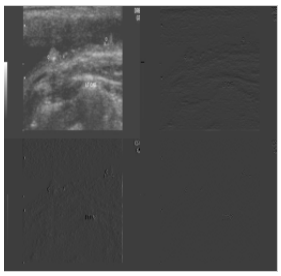


Figure (9): Biorthogonal

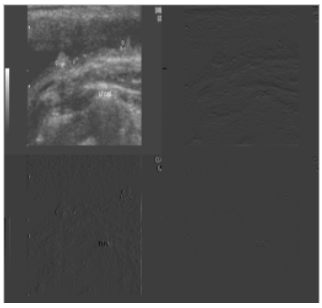


Figure (10): db Output

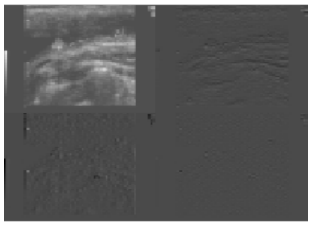


Figure (11): Haar

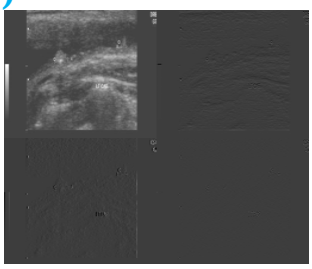


Figure (12): Compared output

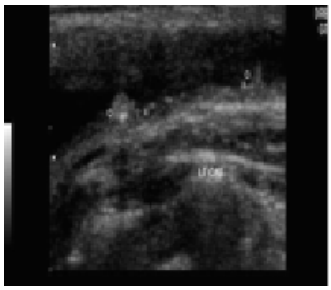
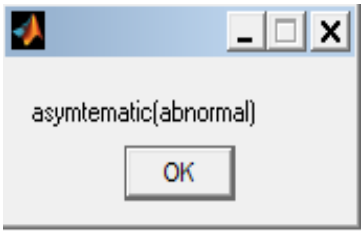


Fig.13.Approximation



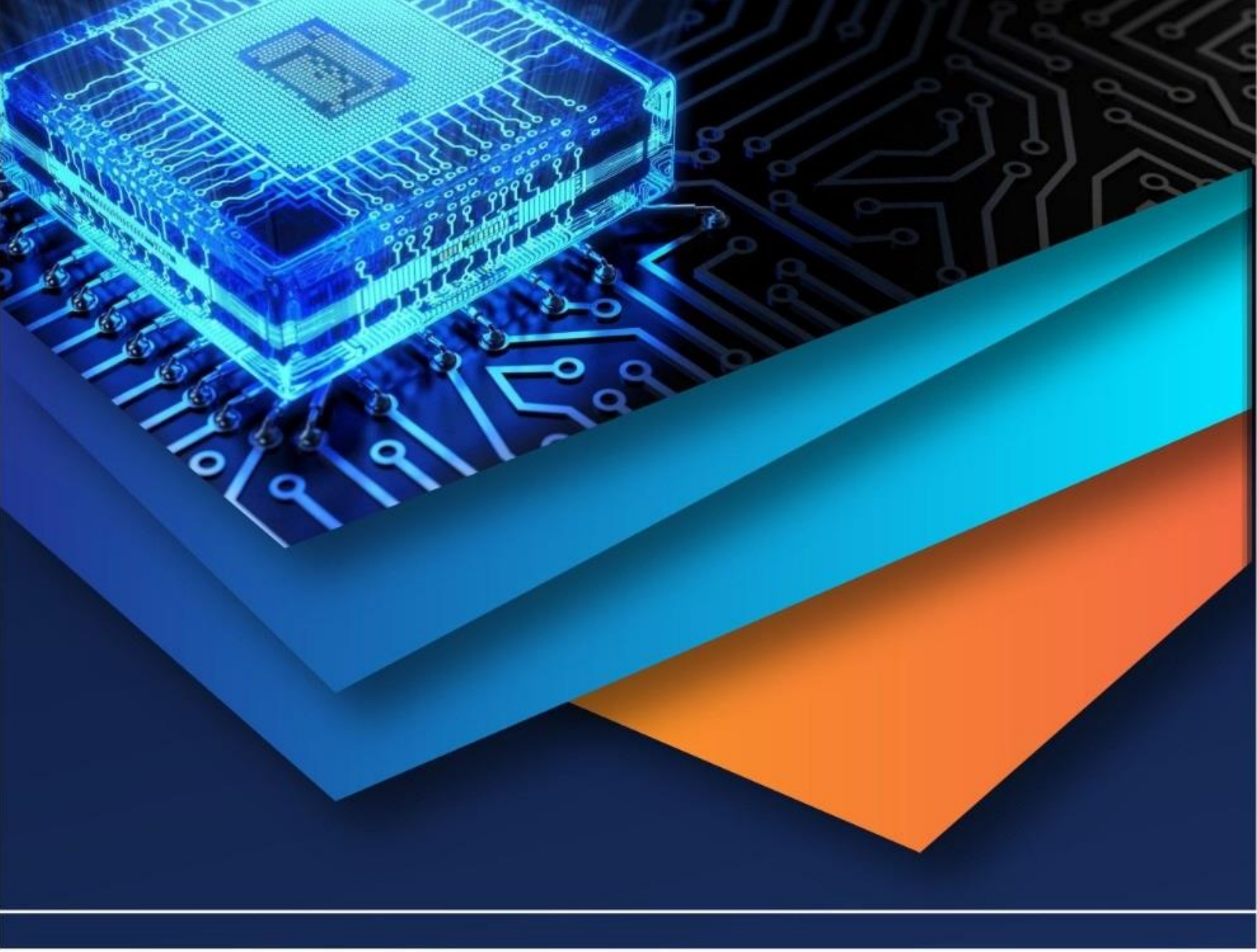
Component

V. CONCLUSION

It is very difficult to diagnose the symptomatic and asymptomatic plaques from ultrasound images using image processing. Currently, only experienced physicians or vascular ultra sonographers have the ability to efficiently detect these differences during ultrasound scans. Our system can be used as a diagnostic tool in modern clinical practice since it can provide decision support with regard to carotid plaque treatment. Our system uses DWT for feature extraction and can diagnose the two classes automatically with an accuracy, sensitivity, and specificity of more than 83%. We have achieved a classification accuracy of 83.7%, sensitivity of 80%, and specificity of 86.4%. This accuracy is relatively higher than those recorded in similar studies in the literature.

REFERENCES

[1] N. R. Sims and H. Muyderman, "Mitochondria, oxidative metabolism and cell death in stroke," Biochim. Biophys. Acta., vol. 1802, no. 1, pp. 80–91, Jan. 2010.
[2] D. W. Droste, M. Karl, R. M. Bohle, and M. Kaps, "Comparison of ultrasonic and histopathological features of carotid artery stenosis," Neurol. Res., vol. 19, no. 4, pp. 380–384, Aug. 1997.
[3] D. R. Labarthe, Epidemiology and Prevention of Cardiovascular Diseases: A Global Challenge. Gaithersburg, MD: Aspen, 1998.
[4] Y. Nagai, K. Kitagawa, M. Sakaguchi, Y. Shimizu, H. Hashimoto, H. Yamagami, M. Narita, T. Ohtsuki, M. Hori, and M. Matsumoto, "Significance of earlier carotid atherosclerosis for stroke subtypes," Stroke, vol. 32, no. 8, pp. 1780–1785, Aug. 2001.
[5] A. Maton, J. Hopkins, C. W. McLaughlin, S. Johnson, M. Q. Warner, D. LaHart, and J. D. Wright, Human Biology and Health. Englewood Cliffs, NJ: Prentice-Hall, 1993.
[6] L. A. Solberg, P. A. McGarry, J. Moossy, J. P. Strong, C. Tejada, and A. C. Löken, "Severity of atherosclerosis in cerebral arteries, coronary arteries, and aortas," Ann. NY Acad. Sci., vol. 149, no. 2, pp. 956–973, Nov. 1968.
[7] A. M. Pancioli, J. Broderick, R. Kothari, A. Tuchfaber, R. Miller, J. Khoury, and E. Jauch, "Public perceptions of stroke warning signs and knowledge of potential risk factors," JAMA, vol. 279, no. 16, pp. 1288– 1292, Apr. 1998.
[8] T. Craven, J. E. Ryu, M. A. Espeland, F. R. Kahl, W. M. McKinney, J. F. Toole, M. R. Mc Mahan, C. J. Thompson, G. Heiss, and J. R. Crouse, Jr., "Evaluation of the associations between carotid artery atherosclerosis and coronary artery stenosis: A case-control study," Circulation, vol. 82, no. 4, pp. 1288–1292, Oct. 1990.
[9] I. Kallikazaros, C. Tsioufis, S. Sideris, C. Stefanadis, and P. Toutouzas, "Carotid artery disease as a marker for the presence of severe coronary artery disease in patients evaluated for chest pain," Stroke, vol. 30, no. 5, pp. 1002–1007, May 1999.
[10] B. Lerfeldt, M. Forsberg, C. Blomstrand, D. Mellström, and R. Volkmann, "Cerebral atherosclerosis as predictor of stroke and mortality in representative elderly population," Stroke, vol. 33, no. 1, pp. 224–229, Jan. 2002.



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY