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CLASSIFICATION OF CAROTID PLAQUE USING ULTRASOUND IMAGE FEATURE ANALYSIS

V.Bhuvaneshwari[1] and D.Sasikala[2]

[1]*PG scholar, ECE Department, Vivekanandha college of engineering for women*

[2]*Associate Professor, ECE Department, Vivekanandha college of engineering for women*

Abstract--The aim of this study was to evaluate the risk of stroke by classifying the carotid plaques using ultrasound image feature analysis. Plaque is a buildup of White Blood Corpuscles, deposits within the wall of an artery. Plaques are generally classified into two types namely Symptomatic and Asymptomatic. Classification is done in order to predict the risk of stroke in early stages. In order to reduce the high degree of risk of stroke, techniques are needed to effectively classify the plaque tissues. Then for the classification, carotid plaque image features are needed. Then the carotid plaques image features are extracted using Gray-Level-Co-occurrence Matrix and extracted features are given to the classifier and the accuracy of Risk of stroke was evaluated.

***Keywords*: Assessment of stroke risk; carotid plaque; Ultrasound image analysis; Classification**

I. INTRODUCTION

During the last 20 years, the introduction of computer aided methods and image standardization has improved the objective assessment of carotid plaque echogenicity and heterogeneity, and has largely replaced subjective assessment that had been criticized for its poor reproducibility.

Then on the estimation from World Health Organization shows that by 2030 almost 23.6 million people will die because of the cardiovascular disease, where the atherosclerosis is the result of accumulation of plaque formed in the carotid artery wall.

Until now several studies presenting classification models for carotid ultrasound images have been presented, but none of these methods provide any valid confidence measures on this problem.

In order to address this, the improved classifier is used and classifying the carotid plaque, to give the confidence measure and assess the Risk of stroke based on carotid plaque feature extracted using Gray-Level-Co-occurrence Matrix. In this work, the different classifiers are used in order to evaluate the performance of Conformal Predictors on these problems.

For this application, images were recorded from 137 asymptomatic and 137 symptomatic plaques .Two feature sets are extracted from plaques: The first based on morphological image analysis and the second based on texture analysis.Four popular classification methods were using namely Artificial Neural Network(ANN), Support vector Machine(SVM), Naive Bayes Classification (NBC), and K-Nearest Neighbours.Then by comparing the results and showing the reliability and accuracy of risk of stroke from the classification of atherosclerotic carotid plaques.

Earlier studies have been primarily focused on basic statistical features such as the gray scale median (GSM).Gray Scale Median Gray Scale Median was found to be very successful in differentiating between symptomatic and asymptomatic cases.

Other approaches that can provide some kind of confidence measures include Bayesian methods and the Probably Approximately Correct (PAC) theory. Nevertheless, these approaches have some drawbacks that can hinder application. Several classification techniques have been used for the classification of carotid plaques, such as Multilayer Perceptron (MPL) Neural Networks. Self Organizing Map (SOM) Networks, Radial Basis Function (RBF) Networks, Probabilistic Neural Networks (PNNs), Support Vector Machines (SVMs) and k-Nearest Neighbors. In addition, research has been done on simple statistical analysis of the plaque characteristics.

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Here the work is done under the flow which is shown in figure 1.1 which shows the performance of work. That is initially ultrasound carotid plaque images were taken and by using GLCM method the features are extracted and the extracted feature values are given to the classifiers and the performance plot was obtained and compared in order to evaluate the risk of stroke. Then not only GLCM features are used the various methodology used features were also used.

The performance and working of this work was represented by the following block diagram

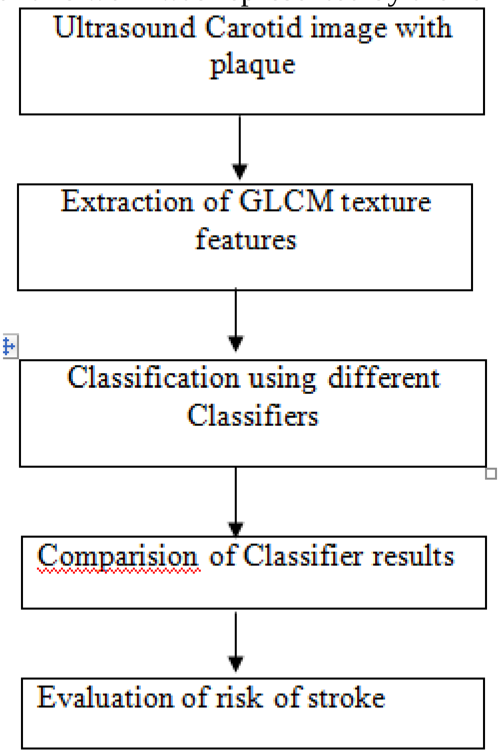

Figure 1.1 Block diagram of work

II. EXTRACTION OF FEATURES

Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. When performing analysis of complex data one of the major problem stems from the number of variables involved. Analysis with a large number of variables generally required a large amount of memory and computations of the variables to get around these problems while still describing the data with sufficient accuracy.

Feature extraction is method of capturing visual content of images for indexing and retrieval.The carotid plaque features are extracted using Gray-Level-Co-occurrence Matrix method. By using this method features like Homogeneity, Contrast energy, Entropy were extracted. The Homogeneity means the calculation of relativity uniformity in a substance. Contrast says about the difference, dissimilarities. Energy and Entropy the measure of the level of disorder in a closed but changing system, a system in which energy can only be transferred. Gray-Level-Co-occurrence Matrix method is used since of its less computation time, High efficiently used for real time Pattern Recognition application.

Texture analysis aims in finding a unique way of representing the characteristics of texture and represent them in unique form, so used for classification and segmentation. These four features Homogeneity, contrast, energy and entropy provides high discrimination accuracy required for the estimation.

Classifiers: Classification is done since the Symptomatic patients have high degree of risk of stroke, so techniques are needed to effectively classify the plaque tissues. Then Used for further treatment process. Because each class of plaque has unique of process for treatment. Symptomatic-carotid endartrectomy (CEA)- a surgical process for the removal plaque inside the artery, where as Asymptomatic-inserting slender metal mesh tube which expands the narrowed carotid artery.

Artificial Neural Networks

A neural network is a machine that is designed to model the way in which the brain performs a particular task or function of interest. The network is usually implemented by using electronic components or is simulated in software on digital computer. It is a massive interconnection of simple computing cells referred to as Neurons or processing unit.

Artificial Neural Networks (ANNs) are networks of interconnected neurons. Determines the intensity of the signal traveling through the connection. Each connection is associated with the weight. These weights are adjusted during training to reduce the output error of the network. The output layer of a neural network has a neuron for each possible class, and given an instance and predict the class corresponding to the output neuron which gives the highest values.

A probabilistic neural network (PNN) is predominantly a classifier Map any input pattern to a number of classifications can be forced into a more general function approximator it is an implementation of a statistical algorithm called kernel discriminant analysis in which the operations are organized into a multilayered feed forward network with four layers, Input layer, Pattern layer, Summation layer, Output layer.

Support vector machine

Support Vector Machines (SVMs). It fix a separating hyperplane that margin between them. This classifier use a kernel mapping function. where the instances are mapped to higher dimensional space such that a linear separation can be made. For the purpose of building a conformal prediction support vector machine method was used.

Naive Bayes Classifier

It is the assumption of attribute independence. Redundancies will be removed using this classifier. This Naive Bayes Classifier (NBC) is named after Bayes Theorem, and the Naive assumption of attribute independence. This classifier is applicable for many real- world datasets. Its output probability defines a non-conformity measure and build the conformal prediction.

Nearest Neighbors

The training set consists of the test instance and the distance between the test instance from the other instance that are provided are computed. For more accurate non-conformity measures we consider the distances of the k-nearest instances that belong to other classes.

III. RESULTS OF NEURAL NETWORK CLASSIFIER

Thus the input image used in this system is a common carotid artery with symptomatic plaque and asymptomatic plaque which is captured by the ultrasound scanner. One of the input image of symptomatic and asymptomatic are shown in figure 3.1 and figure 3.2

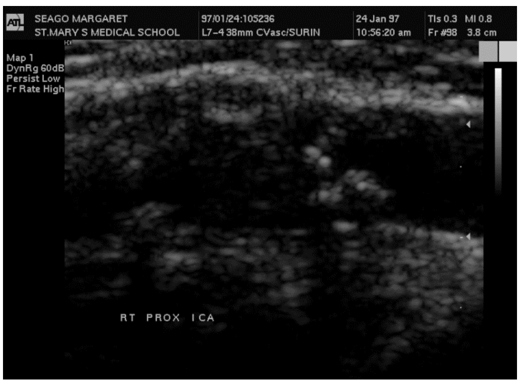

Figure 3.1 Symptomatic input image

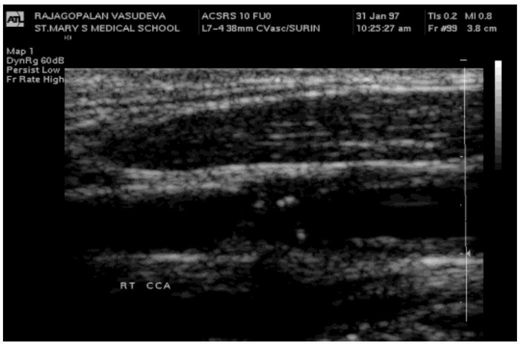

Figure 3.2 Asymptomatic input image

For symptomatic horizontal features were extracted and for 0° and 30° orientation result was shown in Table 3.3, 3.4 for one ultrasonic plaque image

GLCM Feature values			
Scale	Orientation	Contrast	correlation
1	0	0.26128529	0.812030543
2	0	0.75390836	0.858446948
3	0	1.03950915	0.859767735
4	0	1.15606469	0.854429117
5	0	1.18869343	0.85263477
1	30	0.26996737	0.830309983
2	30	0.70523479	0.862433325
3	30	1.0297489	0.867315503
4	30	1.14111221	0.855439084
5	30	1.18818272	0.852717166

Table 3.3 Feature values using GLCM for symptomatic plaque images.

GLCM Feature values			
Scale	Orientation	energy	homogeneity
1	0	0.3227925	0.909950584
2	0	0.12704268	0.805538138
3	0	0.08259477	0.757367746
4	0	0.07381826	0.745310682
5	0	0.07211784	0.742290869
1	30	0.31327533	0.911448432
2	30	0.13734159	0.814637537
3	30	0.08652081	0.758367989
4	30	0.07465094	0.74681326
5	30	0.07205879	0.742159644

Table 3.4 Feature values using GLCM for symptomatic plaque images

For asymptomatic vertical features were extracted and for 0° and 30°orientation result was shown in table3.4 and table3.5 for one ultrasonic plaque image.

GLCM Feature values			
Scale	Orientation	Contrast	correlation
1	0	0.638502	0.81328761
2	0	0.683217	0.88086041
3	0	0.915123	0.88287844
4	0	0.950731	0.86761119
5	0	0.85903	0.88362476
1	30	0.615804	0.83065158
2	30	0.653341	0.88088979
3	30	0.883317	0.88413923
4	30	0.983444	0.87439423
5	30	0.859342	0.88366212

Table 3.5 Feature values using GLCM for asymptomatic plaque images

GLCM Feature values			
Scale	Orientation	energy	homogeneity
1	0	0.3112252	0.893847827
2	0	0.1215801	0.817787866
3	0	0.0815803	0.774422613
4	0	0.0841185	0.775429848
5	0	0.0823327	0.776719393
1	30	0.3021253	0.898081052
2	30	0.1299151	0.824800917
3	30	0.0842724	0.779518844
4	30	0.0822198	0.769493309
5	30	0.0822834	0.776753677

Table 3.6 Feature values using GLCM for symptomatic plaque image.

Here the neural network training tool was displayed after running then from the that the performance plot, validation result and training sets are obtained for both the symptomatic and asymptomatic image.
The neural network performance for vertical features values obtained by GLCM, it has the four layers, input layer, hidden layer, summation layer, output layer. The operations are organized into a multilayered feed forward network with that layers. Result give the time taken for performing, performance range, gradient.

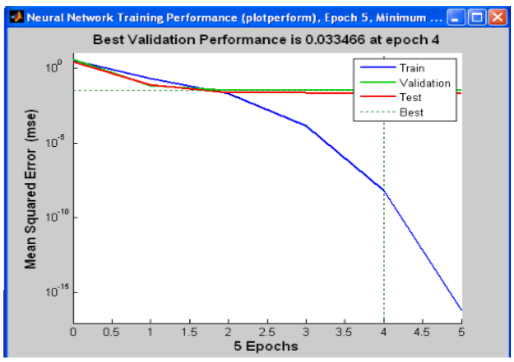

Figure 3.7 Performance plot for GLCM horizontal features

Performance plot was obtained after the minimum gradient was achieved and says about the train range, validation, test values between the mean square value and epochs.

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The validation result is used to detect the presence and identify the location and magnitude of faults (biases) in sensed readings.
The neural network performance for horizontal features values obtained by GLCM, it has the four layers, input layer, hidden layer, summation layer, output layer. The operations are organized into a multilayered feed forward network with that layers. Result give the time taken for performing, performance range, gradient.

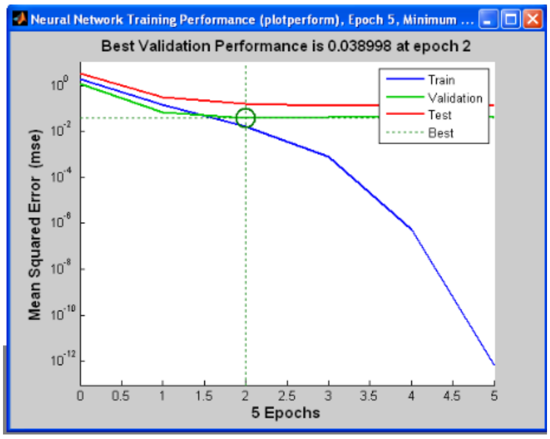

Figure 3.8 Performance plot for GLCM vertical features

Performance plot was obtained after the minimum gradient was achieved and says about the train range, validation, test values between the mean square value and epochs.
The validation result is used to detect the presence and identify the location and magnitude of faults (biases) in sensed readings.
Training set can be made easily directly from the time series. Certain number of measured values is used as inputs and the value to be predicted is used as required output. Input part of the time series is called window, the output part is the predicted value. By shifting the window over time series the items of training set .It is advised to left part of time series for testing, i.e., to not use this part during learning, but to use it to test how successfully the network learned to predict our data.
Then again a set of horizontal and diagonal set of features are extracted by using the GLRS method. Then the sample feature values are shown below in table3.9 and 3.10 .
For symptomatic horizontal features were extracted and for 0° and 30° orientation result was shown in Table 3.9, 3.10,3.11 for one ultrasonic plaque image

GLRS Feature values			
Scale	Orientation	SRE1	LRE1
1	0	0.03894	65240.8
2	0	0.011497	67599.09
3	0	0.039487	65697.68
4	0	0.034243	65694.22
5	0	0.034243	65694.22
1	30	0.021739	67619.54
2	30	0.033583	66183.53
3	30	0.034243	65694.22
4	30	0.034243	65694.22
5	30	0.034243	65694.22

Table 3.9 Feature values using GLRS for symptomatic plaque images.

GLRS Feature values				
Scale	Orientation	GLN1	RP1	RLN1
1	0	266.8403	0.00407	238.8194
2	0	266.259	0.003929	247.0935
3	0	266.6993	0.004042	240.4895
4	0	266.6993	0.004042	240.4336
5	0	266.6993	0.004042	240.4336
1	30	266.259	0.003929	248.9928
2	30	266.5704	0.004014	243.9084
3	30	266.6993	0.004042	240.4336
4	30	266.6993	0.004042	240.4336
5	30	266.6993	0.004042	240.4336

Table 3.10 Feature values using GLRS for symptomatic plaque images

GLRS Feature values			
Scale	Orientation	LGRE1	HGRE1
1	0	0.971354	1.114583
2	0	0.983813	1.064748
3	0	0.973776	1.104895
4	0	0.973776	1.104895
5	0	0.973776	1.104895
1	30	0.983813	1.064748
2	30	0.976232	1.09507
3	30	0.973776	1.104895
4	30	0.973776	1.104895
5	30	0.973776	1.104895

Table 3.11 Feature values using GLRS for symptomatic plaque images

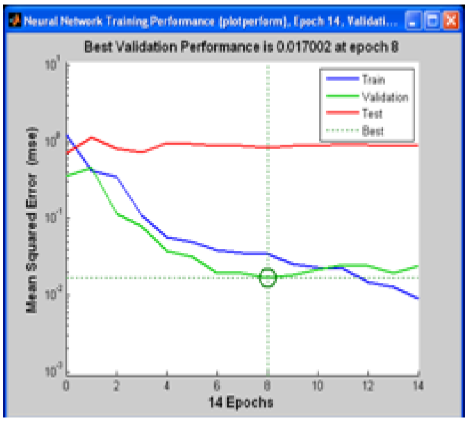

Figure 3.12 Performance plot for GLRS horizontal features

For asymptomatic diagonal features were extracted and for 0° and 30°orientation result was shown in table 3.13 , 3.14,3.15 for one ultrasonic plaque image.

GLRS Feature values			
Scale	Orientation	SRE1	LRE1
1	0	0.213601	35162.27
2	0	0.210271	39954.68
3	0	0.217314	38830.81
4	0	0.232509	38126.09
5	0	0.238754	37816.01
1	30	0.204121	40591.29
2	30	0.223559	39000.02
3	30	0.234933	37750.48
4	30	0.235416	37982.4
5	30	0.235416	37982.4

Table 3.13Feature values using GLRS for symptomatic plaque images

GLRS Feature values				
Scale	Orientation	GLN1	RP1	RLN1
1	0	315.095	0.00684	100.7231
2	0	299.1422	0.006162	122.4541
3	0	302.3229	0.006303	118.4888
4	0	304.9251	0.006416	121.2555
5	0	306.2445	0.006473	122.1004
1	30	297.2744	0.006077	124.4605
2	30	302.3229	0.006303	123.4036
3	30	306.2445	0.006473	121.1354
4	30	305.5833	0.006445	121.7237
5	30	305.5833	0.006445	121.7237

Table 3.14Feature values using GLRS for symptomatic plaque images

GLRS Feature values			
Scale	Orientation	LGRE1	HGRE1
1	0	0.831095	1.67562
2	0	0.853784	1.584862
3	0	0.848655	1.605381
4	0	0.844714	1.621145
5	0	0.842795	1.628821
1	30	0.856977	1.572093
2	30	0.848655	1.605381
3	30	0.842795	1.628821
4	30	0.84375	1.625
5	30	0.84375	1.625

Table 3.15Feature values using GLRS for symptomatic plaque images

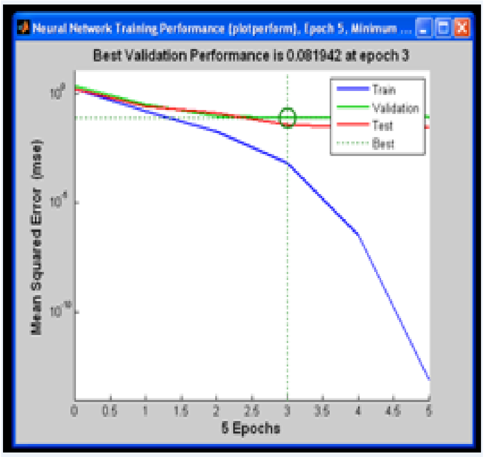

Figure 3.16 Performance plot for GLRS Diagonal features

Thus the performance result shows the differences and in further the other features are extracted and given to the other classifiers and the performances are compared and the risk was evaluated.

Discussion

The features extracted from the plaque images and given to the classifiers. Then the classification is done and the classifier results are compared and analysed in order to evaluate the stroke of risk. In the earlier studies based on the comparison study of Different pattern classifiers the k-nearest neighbours classifier and Parzen Window classifier were used but there was the accuracy of only 13.5%. Then in the study based on Combining classifiers in rock image classification supervised and unsupervised approach ,the product rate was not included into comparizion because of the probability estimation in k- nearest neighbours classifier was zero. Then there was result corruption occurs and the accuracy was only 68%.Then similar to these studies there was many methods and techniques for the classification but there was less accuracy.

IV. CONCLUSION

In the evaluation of risk of stroke the carotid plaque features were extracted and then they were classified in order to obtain the accuracy. The existing will be very much applicable and useful to predict the risk of stroke earlier stage and will be able to reduce the death rate occurs due to the atherosclerotic carotid plaque. Here the accuracy rate will be increased so as to predict the degree of risk of stroke.

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