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Optimal Classifier for the Diagnosis of Breast Cancer using Computational Intelligence Techniques

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ABSTRACT: In this paper a new classification algorithm is proposed for the Efficient Classification of Breast Tumor. In order to develop algorithm 33 CT scan images of patients have been considered consisting of Benign Tumor, Malignant Tumor and Normal Breast Computed tomography (CT) Scan image. With a view to extract features from the CT scan images after image processing, an algorithm proposes (WHT) Wavelet Transform coefficients. The Efficient classifiers based on Multilayer Perceptron (MLP) Neural Network. A separate Cross-Validation dataset is used for proper evaluation of the proposed classification algorithm with respect to important performance measures, such as MSE and classification accuracy. The Average Classification Accuracy of MLP Neural Network comprising of one hidden layers with 1 PE's organized in a typical topology is found to be superior (100 %) for Training . Finally, optimal algorithm has been developed on the basis of the best classifier performance. The algorithm will provide an effective alternative to traditional method of Breast Computed tomography (CT) scan image analysis for deciding the tumor in Breast is Benign or Malignant.

KEYWORDS: Neural solution, MatLab, Excel, CT scan images.

I. INTRODUCTION

The early detection of Breast cancer is a most challenging problem to identify in human body, due to the different -different cells structure of cancer, where most of the cells are overlapped with each other. Cancer diagnosis is one of the most danger problems in the medical domain. Most of researchers have focused try to improve performance and possible to obtain Best and satisfactory results. The correct classification of cancer is an important real-world medical problem. Cancer has become one of the most harmful Death disease around the world and research into Breast cancer diagnosis and treatment has become an one of the most important issue all over the world.

In the modern age of computerized fully automated trend of living, the field of automated diagnostic systems plays an important and vital role. Automated diagnostic system designs in Medical Image processing are one such field where numerous systems are proposed and still many more under conceptual design due explosive growth of the technology today [1].. More people die because of Breast cancer than any other types of cancer such as Breast, colon, and prostate cancers. There is significant evidence indicating that the early detection of Breast cancer will decrease death rate [2].

The proposed algorithm provides Efficient Classification of Breast Tumor based on (M L P) Multi-layer Perceptron neural network ap- proach and tested on the Breast 33 CT scan images comprising of features extracted using (DCT) discrete cosine Transform domain co-efficient .

II. RELATED WORK (LITERATURE SURVEY)

1] Artificial Neural Networks classifiers have been used in a variety of applications ranging from industrial automation to medical diagnosis by authors. Because of its characteristics like fast learning, adaptability, fault tolerance, solving complex non linear problems efficiently, good recognition Neural Networks are being used in the medical domain to benefit the medical fraternity and patient's community alike, as opposed to the conventional methods. In the present paper we have conducted a survey which includes a detailed review of the various applications where Neural Networks

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have been used in Breast Cancer diagnosis in the recent years. Neural Networks classifiers have been used in a medical diagnosis because of its characteristics like fast learning.

2] Authors used a Computer-Aided Diagnosis System for Digital Mammograms Based on Fuzzy-Neural and Feature Extraction Techniques The system is capable of detecting nodules when they are in their initial stages, facilitating their early diagnosis, thus, improving the patients probability.

3] Authors used Imaging of Breast Cancer with Optical Coherence Tomography Needle Probes .The method used Interstitial imaging, needle probe, OCT needle, optical coherence tomography (OCT). To enable a clear delineation of tumor boundary from surrounding adipose tissue and identification of microarchitectural features.

4] Authers used Computer-Aided Diagnosis of Solid Breast Nodules:Use of an Artificial Neural Network Based on Multiple Sonographic Features .The developed CAD algorithm has the potential to increase the specificity of US for characterization of breast lesions.

III. PROPOSED ALGORITHM

A. Research methodology *:*

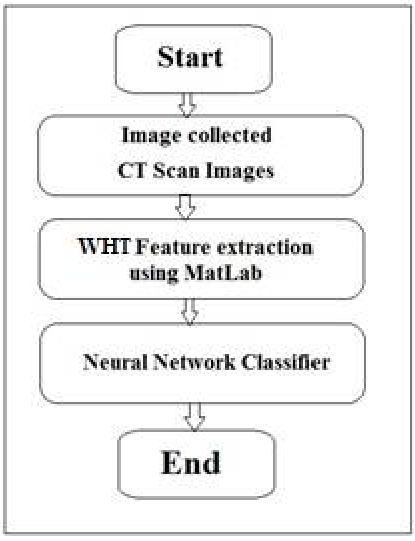

Figure 1: Methodology of work

It is proposed to study Efficient Classification of Breast Tumor using Neural Classifier. Data acquisition for the proposed classifier designed for the diagnosis of Breast Cancer shall be in the form of CT Scanned images. Image data will be Collected from the different- different hospitals of the country .The most important un correlated features as well as coefficient from the images will be extracted .In order to extract features, statistical techniques, image processing techniques, transformed domain will be used.

1) Images Collected

We have collected the 33 CT-Scan images of Breast cancer from the private hospital. By using this CT scan images an algorithm is developed which proposes two-dimensional Wavelet (WHT) Transform domain coefficients in addition to Average, Standard Deviation, Entropy, Contrast, Correlation, Energy, Homogeneity total coefficients i get in excel sheet by using matlab code.

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2) Feature Extraction

Collected Breast tumor CT Scan images are in .jpg format. By using CT scan images processing & cropping the region of Tumor the 128 features are extracted .

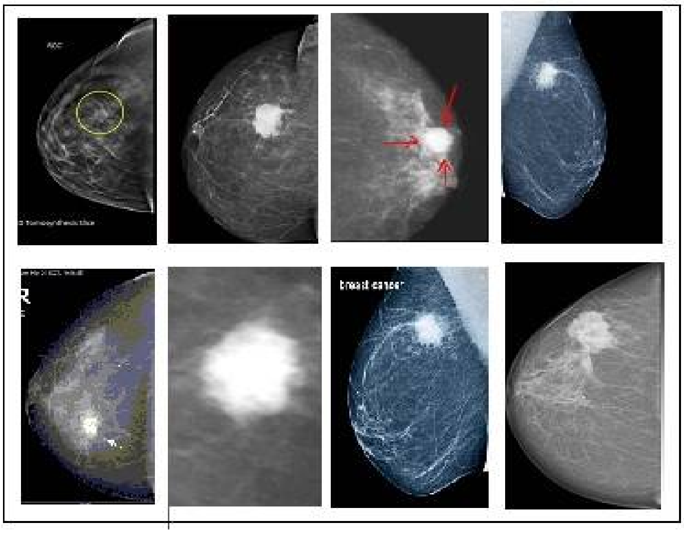

Fig. 2: Few Samples of input processed CT scan images of Breast tumor.
(Above Breast images are of Benign, Malignant)

Each Breast CT image is represented by a feature vector, F; which is comprised of 128 different parameters. The dataset contains 33 instances (exemplars) for three different classification The classifier based on neural network is trained from the training dataset, where a feature vector is mapped on to a particular class or name of the Breast disease. The neural network learns from data (training exemplars) and the connection weights and biases are estimated as a result of this learning.

3) Neural Networks

Following Neural Networks are tested:

a) Multilayer perceptron (MLP)

The most common neural network model is the multi layer perceptron (MLP). This type of neural network is known as a supervised network because it requires a desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown. A graphical representation of an MLP is shown below:

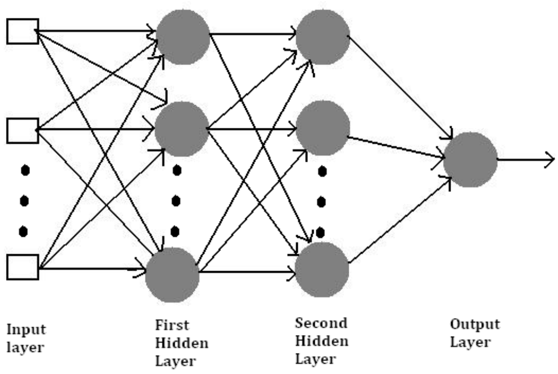

Fig 3. The structure of neural network model multi layer perceptron (MLP)

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The MLP and many other neural networks learn using an algorithm called backpropagation. With backpropagation, the input data is repeatedly presented to the neural network. With each presentation the output of the neural network is compared to the desired output and an error is computed. This error is then fed back (backpropagated) to the neural network and used to adjust the weights such that the error decreases with each iteration and the neural model gets closer and closer to producing the desired output. This process is known as "training". [10]

- **Learning Rules used**:
  - **Momentum(MOM)**

Momentum simply adds a fraction m of the previous weight update to the current one. The momentum parameter is used to prevent the system from converging to a local minimum or saddle point. A high momentum parameter can also help to increase the speed of convergence of the system. However, setting the momentum parameter too high can create a risk of overshooting the minimum, which can cause the system to become unstable. A momentum coefficient that is too low cannot reliably avoid local minima, and can also slow down the training of the system.

  - **Conjugate Gradient (CG)**

CG is the most popular iterative method for solving large systems of linear equations. CG is effective for systems of the form A=xb-A (1) where x _is an unknown vector, b is a known vector, and A _is a known, square, symmetric, positive-definite (or positive-indefinite) matrix. (Don't worry if you've forgotten what "positive-definite" means; we shall review it.) These systems arise in many important settings, such as finite difference and finite element methods for solving partial differential equations, structural analysis, circuit analysis, and math homework.

Developed by Widrow and Hoff, the delta rule, also called the Least Mean Square (LMS) method, is one of the most commonly used learning rules. For a given input vector, the output vector is compared to the correct answer. If the difference is zero, no learning takes place; otherwise, the weights are adjusted to reduce this difference. The change in weight from ui to uj is given by: dwij = r* ai * ej, where r is the learning rate, ai represents the activation of ui and ej is the difference between the expected output and the actual output of uj. If the set of input patterns form a linearly independent set then arbitrary associations can be learned using the delta rule.

It has been shown that for networks with linear activation functions and with no hidden units (hidden units are found in networks with more than two layers), the error squared vs. the weight graph is a paraboloid in n-space. Since the proportionality constant is negative, the graph of such a function is concave upward and has a minimum value. The vertex of this paraboloid represents the point where the error is minimized. The weight vector corresponding to this point is then the ideal weight vector.

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  - **Quick propagation**

Quick propagation (Quickprop) [1] is one of the most effective and widely used adaptive learning rules. There is only one global parameter making a significant contribution to the result, the e-parameter. Quick-propagation uses a set of heuristics to optimise Back-propagation, the condition where e is used is when the sign for the current slope and previous slope for the weight is the same.

  - **Delta by Delta**

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IV. SIMULATION RESULTS

1) Computer Simulation

The MLP neural network has been simulated for 33 tumor CT Scan images out of which 29 (90% of total images) were used for training purpose and 4 (10% of total images) were used for cross validation.
The simulation of best classifier along with the confusion matrix is shown below :

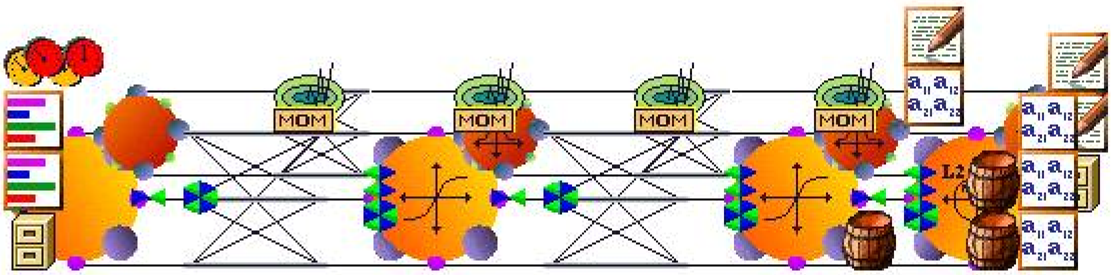

Fig.4 MLP neural network trained with MOM learning rule

2) Results :

Here Table I and Table II Contend the C.V (cross validation) as well as Training data set. B stand for Benign And M stand For Malignant tumor identification.

Output / Desired	*NAME(B)*	*NAME(M)*
NAME(B)	2	0
NAME(M)	0	2

Table I. Confusion matrix on CV data set

Output / Desired	*NAME(B)*	*NAME(M)*
NAME(B)	14	0
NAME(M)	0	15

TABLE II. Confusion matrix on Training data set

Here Table III and Table IV Contain the Training and C.V result. Table III show the result or identify the Benign and Malignant 100% or Table IV show the result or identify the Benign and Malignant 100%.

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Performance	*NAME(B)*	*NAME(M)*
MSE	3.757E-05	3.757E-05
NMSE	0.00015028	0.00015028
MAE	0.005319189	0.005319189
Min Abs Error	0.002192226	0.002192228
Max Abs Error	0.0103443	0.010344299
R	0.999942337	0.999942337
Percent Correct	100	100

TABLE III. Accuracy of the network on CV data set

Performance	*NAME(B)*	*NAME(M)*
MSE	1.54785E-05	1.54785E-05
NMSE	6.19878E-05	6.19878E-05
MAE	0.003695769	0.003695769
Min Abs Error	0.000786962	0.000786963
Max Abs Error	0.005602442	0.005602441
r	0.999969125	0.999969125
Percent Correct	100	100

TABLE IV. Accuracy of the network on training data set

Here, Table V Show the Finale results of this paper.

Learing Rule	Processing Elements	Training		Cross Validation	
		Benign	Malignant.	Benign	Malignant.
MOM	1	100%	100%	100%	100%

TABLE V. Multilayer Perceptron Neural Network Transform Domain : (WHT) Wavelet Transform

Here Table V Show the Finale result of this paper .It show the 1 Processing element with Momentum algorithm of Neuro Solution. it show the Benign 100% in C.V and Trainign and Malignant 100% in both of them.

V. Conclusion and Future Work

The MLP classifier with MOM learning rule gives best performance of 100% in Training for malignant and benign tumor is 100% and in Cross validation 100% benign and 100% Malignant.

Using our Algorithm, Doctor can Classified Breast cancer with enough confidence. Moreover, our Algorithm can also be used by the experts in order to confirm their decision.

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