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Thermogram Analysis Using MLP Network

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Abstract—

This research paper presents a novel approach for analysis of breast thermograms for detection of tumour using Artificial Neural Networks. A Multilayer feed forward Perceptron is designed to classify the thermal images captured using an infrared camera into normal, benign and malignant. The network is trained with 65 thermograms and tested and validated for 10 thermograms. Using Supervised learning a performance efficiency of 85% is achieved.

Keywords— breast thermograms, Artificial Neural Network, Multilayer feedforward Perceptron, Infrared camera, Supervised learning

I. INTRODUCTION

Breast Cancer is the most widespread cancer among women and its cases are increasing day by day. Mammography which is currently the gold standard for diagnosis of breast cancer has many limitations. It is based on X-ray and has the radiation risk involved. It involves compression of breasts and women therefore complain of pain. It cannot be used for women with surgically altered breasts and is less accurate for young women with dense breast tissue. In a search of other imaging modalities Thermal Imaging is generating an immense interest among researchers. It detects tumour by detecting the heat changes in the underlying tissues due to angiogenesis. It has several advantages such as no radiation involved, no compression and no touching by equipment and technician.

This research work analyses breast thermograms by extracting several features from them such as mean, variance, skewness, kurtosis, entropy, correlation, energy and Histograms. These features are fed to a feedforward Multilayer perceptron which is trained using supervised learning. The network is trained with the features extracted from 65 thermograms and validated using 10 breast thermograms. It classifies the thermograms into normal, benign and malignant for detection of tumour. Once the Artificial Neural Network is properly trained, it can be used to generate consistent output for new sets of inputs reliably and objectively. ANN is widely recognized as a valuable clinical decision support tool. Neural networks are able to capture the complex relationship of variables better than many other models because they capture the non linear relationship of the training data. They have a remarkable ability to derive meaning from complicated or imprecise data and can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques.

The designed MLP has three layers – Input, hidden and output layer and has achieved a performance accuracy of 85%.

II. DEVELOPMENT OF ALGORITHM USING MLP

This section discusses the Classification algorithm developed using the MLP with supervised learning. This learning rule is provided with a set of training data of proper network behaviour. As the inputs are applied to the network, the network outputs are compared to the targets. The learning rule is then used to adjust the weights and biases of the network in order to move the network outputs closer to the targets. The network is trained with backpropagation learning algorithm. During the training process the weights of the output layer and the hidden layer are optimized. An MLP network is said to be fully connected if every node in a given layer is connected to every node in the following layer. MLP's are widely used for pattern classification, recognition, prediction and approximation. MLP can solve problems which are not linearly separable.

The data classification process consists of two phases. In the training phase the network learns to recognize which data vectors belong to given class. In the test phase the network is required to classify correctly vectors that have not been used in the training phase.

The parameters taken for designing the MLP are-

- Layers- MLP is designed with three layers: Input layer, Hidden layer and Output layer.
- Neurons in Input layer- This layer is designed with ten neurons corresponding to the features extracted from the breast thermograms. The neurons in the Input layer correspond to mean, variance, skewness, kurtosis, entropy, joint entropy, Correlation, energy, homogeneity and histogram coefficients.
- Neurons in the Hidden layer- This layer is designed with 12 neurons which have been fixed after experimentation to give maximum accuracy and minimum error.
- Neurons in the Output layer- This layer is designed with 3 neurons corresponding to normal, benign and malignant outputs.
- Hyperbolic tangent sigmoid transfer function is used for the Hidden layer. This function is a good tradeoff for neural networks, where speed is important and the exact shape of the transfer function is not.

- Linear transfer function is used for the activation of the Output layer. It calculates the layer's output from its net input.
- Learning method of the MLP: Supervised back propagation is used as it is built on high mathematical foundation and has very good application potential. In this method the errors for the units of the hidden layer are determined by back propagating the errors of the units of the output layer. Learning occurs in the MLP by changing connection weights after each piece of data is processed, based on the amount of error in the output compared to the expected result.

Figure 1 shows the designed MLP network.

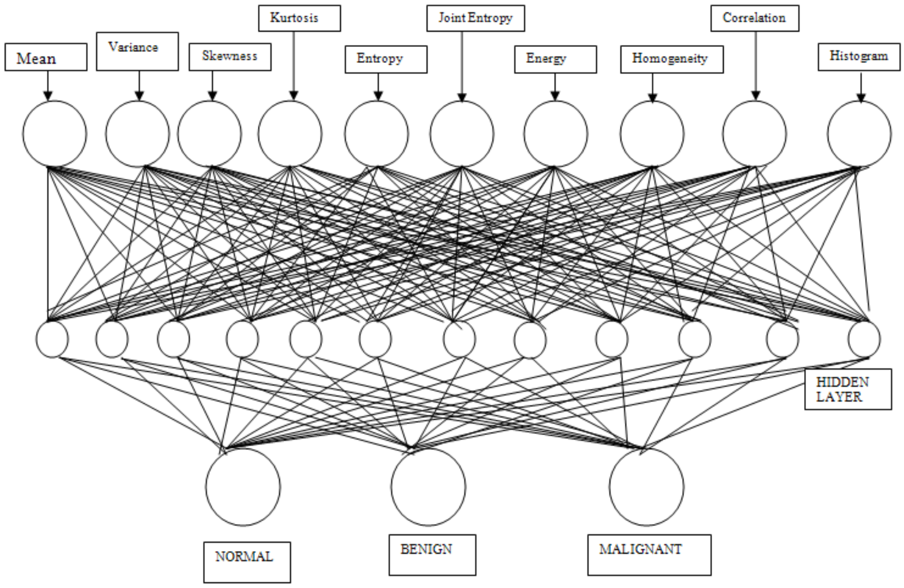

Fig. 1 Designed MLP network

A. Training and testing of the Backpropagation MLP

The MLP is trained for 65 breast thermograms and validated for 10 breast thermograms. The features extracted are fed as input to the network. Before a classifier is trained it has no knowledge in relation to the problem domain. It is through the training process that the input data is mapped to the output vectors and through this process that the network acquires knowledge in the problem domain in question. Once trained, the classifier is then able to generalize and classify using the acquired knowledge. Thus a neural network classifier maintains knowledge about problem domain by the weighted interconnections that were used to train the network. Accordingly it follows that the capabilities of the neural network classifier are heavily dependent on its initial training. Neural networks are able to capture the complex relationship of variables better than many other models because they capture the non linear relationship of the training data. Table I shows the training and testing patterns-

TABLE I TRAINING AND TESTING PATTERNS

Total number of training samples	65
Normal training samples	23
Benign training samples	26
Malignant training samples	16
Testing samples	10

The MLP ANN is trained for 50,000 iterations to minimize the error. The Classifiaction algorithm for the MLP is as follows-

Step I: Perform Feature Extraction from the Breast Thermograms.
Step II: Assign inputs and targets for normal, benign and malignant classes.
Step III: Initialize the network to randomly generate an initial set of weights and biases for the neurons.
Step IV: Assign a set of 10 thermograms to be used for validating the MLP and train the network with data of 65 breast thermograms.
Step IV: With a trained network from step IV, validate the MLP network with the set of test data to generate an output.
Step V: Verify the MLP output with the clinical diagnosis for that patient.

III. CONCLUSIONS

The number of features extracted from the breast thermograms have been increased in this approach as compared to the earlier methods. The neural networks used have been able to classify the thermograms correctly upto a large extent. Features that are visually overlapping also have some distinction between them, that is easily detected by the MLP that facilitates the classification of breast thermograms quickly, efficiently and computationally. In all, it can be concluded that the developed algorithm is useful for computer aided detection of breast abnormality to give a second opinion to the radiologist and overcome the disadvantages of manual analysis .

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