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Feed Forward Back Propagation Neural Network for Detection of Breast Cancer

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ABSTRACT

Breast cancer can be detected at a very early stage by using Breast screening method. First X-ray of each breast is taken, called mammogram. Cancers which are difficult to identify by the doctor or felt by the women herself can be detected through these mammograms. These mammograms can identify the small changes in breast tissue which may cause cancer. The help of technology can improve the diagnosis accuracy. So in this work Feed Forward Back Propagation Neural Network (FFBPNN) classifier is used to classify the mammogram as either benign or malignant. In this process first the mammogram is preprocessed then the mammogram is segmented using K means clustering algorithm, features of segmented mammogram are extracted, the models are built through training and then Feed Forward Back Propagation Neural Network (FFBPNN) classifier is used to classify the mammogram as either benign or malignant.

Keywords :— Mammogram, Preprocess, Segmentation, FFBPNN

I. INTRODUCTION

Breast cancer is one of the main causes of death among women and the most frequently diagnosed non-skin cancer in women [1]. Breast cancer occurs when the cell tissues of the breast become abnormal and uncontrollably divided. These abnormal cells form large lump of tissues, which consequently becomes a tumor [2]. If these disorders are detected at early stage then they could be successfully treated. So it is very much important detect the breast cancer signs as early as possible through appropriate methods.

In most of the hospitals and clinics Mammography method is used to detect the breast cancer at the earliest stage. It has been proven effective to reduce mortality as much as by 30% [6]. The main purpose of screening mammography is to identify the cancerous tumor as early as possible and eliminate it before the establishment of metastases. The early signs for breast cancer are masses and microcalcification but the abnormalities and normal breast tissues are often difficult to be differentiated due to their subtle appearance and ambiguous margin. Only about 3% of the essential information are discovered during a mammogram where a part of suspicious area is enclosed with vessels and normal tissues. This circumstances may cause the radiologists hard to make out a cancerous tumor. To read the mammograms much better and assists the radiologists, computer-aided diagnosis has been developed. Neural Network model can be used in computer-aided diagnosis for mammography interpretation and biopsy decision making.

II. DATA SOURCE

Different types of mammograms are taken from standard MIAS (Mammographic Image Analysis Society) database for training as well as testing purpose. MIAS database of digital mammograms is generated by UK research group. The database contains 161 patients' right and left breast images. So totally the database contains 322 images. To make all the images of same size i.e. 1024 x 1024 pixel the database has been reduced to 200-micron pixel.

III. SYSTEM DESIGN

The various tasks which are carried out in this work are image preprocessing, segmentation, feature extraction, building models through training and then using classifier to classify these images as benign or malignant.

A. Preprocessing

Operations on images at the low level of abstraction are present in image preprocessing. Adaptive histogram equalization is one of the preprocessing methods realized in MATLAB. It is mainly used to improve quality of the image data that suppresses unwanted distortion and it is also used to enhance some image features which are very necessary for further processing of the mammogram. Image information content is not increased by image preprocessing, but the redundancy in the image is used by the image preprocessing. Corresponding to one real object neighboring pixels have the same or similar brightness value. Distorted pixel can be restored in image as an average value of neighboring pixels.
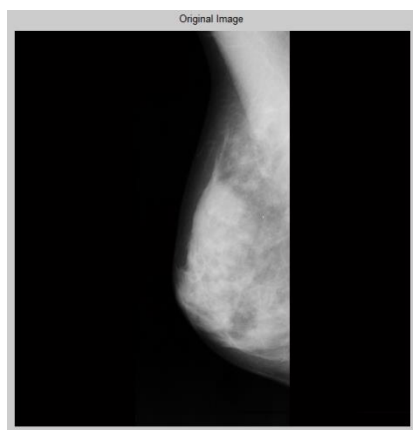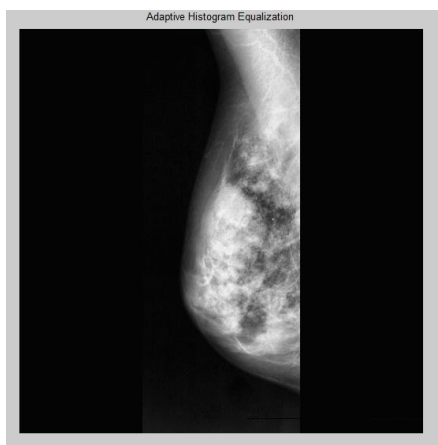
Fig. 1 Original Mammogram

Fig. 2 Mammogram after applying Adaptive Histogram Equalization

Fig. 1 shows the original mammogram selected from standard MIAS database. After application of Adaptive Histogram Equalization mammogram is improved. The improved mammogram is displayed in the fig. 2. In fig. 1 the regions which had low contrast are improved and shown in fig. 2.

B. Segmentation

Dividing an image into distinct regions where the pixels of each region have similar characteristics is called segmentation. The success of image analysis depends on an effective image segmentation process. K-Means clustering algorithm is used to device the segmentation of mammogram. The algorithm works as follows,

K Means clustering algorithm:

Step 1: Number of clusters must be known previously to be K
Step 2: Select K number of cluster centers such that they are farthest apart from each other

$$\mu_i = \underline{\text{some value}} , \ i=1,...,k$$

Step 3: Consider each pixel and assign it to the cluster which is closest

$$c_i = \{ j : d(x_j, \mu_i) \le d(x_j, \mu_l), l \ne i, j=1,...,n \}$$

Step 4: Recalculate cluster centers by finding mean of pixels belonging to the same cluster

$$\mu_i = 1/|c_i| \sum_{j \in c_i} x_j, \ \forall i$$
$$|c| = \text{number of elements in c}$$

Step 5: Repeat step 3 and step 4 till shifting of cluster centers are observed [3].
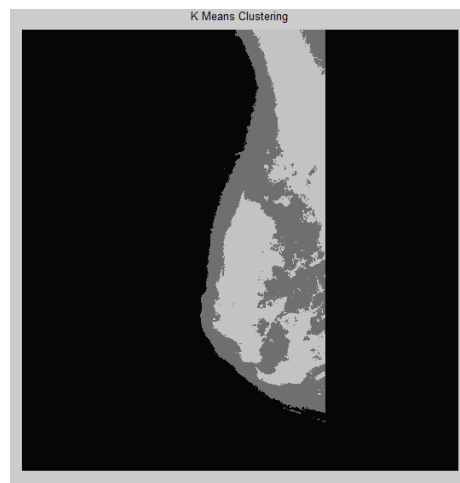

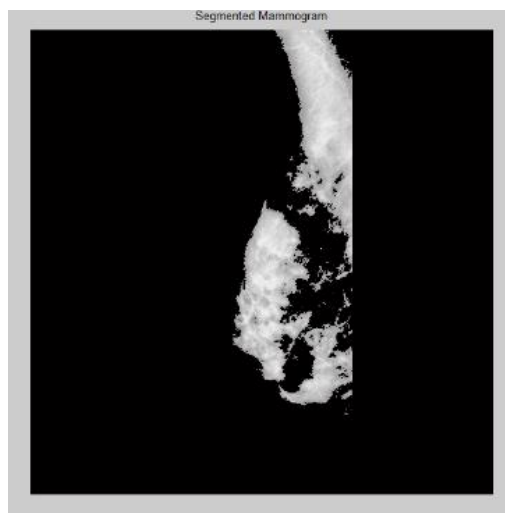Fig. 3 Mammogram after applying K Means Clustering

Fig. 4 Segmented Mammogram

The K Means Clustering algorithm is enforced on the enhanced image. Here the value of K is three. So total three clusters are formed. The clustered image is shown in fig. 3. The black cluster shows the area which is of not at all useful. The gray cluster is also not so important. The brightest cluster shows the area which is of very important. This brightest cluster is selected and segmented. The segmented mammogram is shown in fig. 4.

Image segmentation is a method used in image processing. Mainly, segmentation is done on the raw image to identify small, local, and bright spots. Research done by Kevin et al.

has drawn significant attention on the segmentation process and neural network used [4].

The accuracy of the FFBPNN is tested by having a set of labelled test images for determination of true positive (TP) and false positive (FP) detection rates.

C. Feature Extraction

A discrete cosine transform (DCT) represents a limited sequence of data points in the form of addition of cosine functions fluctuating at various frequencies. DCT is same as DFT and deals with Fourier related transformations, and it only makes use of real numbers. After applying DCT on a mammogram thirty five features are extracted for each mammogram and stored in the database. These features are used by the FFBPNN classifier.

D. Building models through training and Classifier

In this the classifier used is FFBPNN. Let us see how this NN works and how it is trained and implemented.

Facts of Neural Networks (NN) are
- Various layers are present in the NN.
- There is no limit on the number of neurons in every layer.

Structure of a NN is as explained below
- Inputs are applied at the first layer and it called input layer.
- Outputs are produced at the last layer and it is called as output layer.
- Between the input and output layer of NN, there can be any number of hidden layers.
- In most neural network models, a neuron which is present in one layer is connected to all neurons which are present in the next layer.

Basic facts about training of NN
- Provide proper inputs and outputs to train the NN.
- The network learns from the inputs and outputs.
- After the training gets finished, then give proper input to get the output.

NN are parallel data handling frameworks and consists of neurons. All the neurons in NN are arranged in layer format and are associated with each other through links. The brain structure and nervous system of people and creatures are strongly connected; this same system is created in artificial NN also. Axons work is imitated by links in the artificial NN and cells in human body are represented as neurons in artificial NN [5]. Different types of neural networks are there. In this project feed forward neural networks are used. If we take a case of a multilayer Feed Forward Back Propagation Neural Network (FFBPNN) where we are going to provide three inputs and we are going obtain one output. Let these

input values be x_1, x_2, x_3 and output be y as represented in fig. 5.
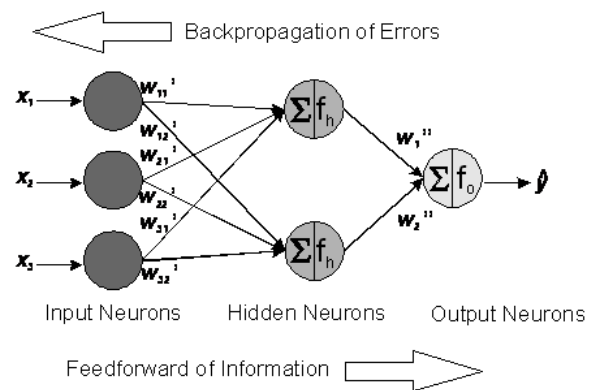

Fig. 5 Representation of FFBPNN

All these values x_1, x_2, x_3 are fed as input to NN, through the connection links it distributes the information. There are weights w'_{ij} known as connection weights present in the middle of input layer and hidden layer, these weights are multiplied to the input values. The function f_h called as activation function gets the input from the hidden neurons. This input is calculated by adding the signals from neurons present at the input layer. The w''_j connections which are present in the middle of neurons of hidden layer and output layer are weighted by resulting activations of neurons present in the hidden layer and propagated to the neuron(s) present in the output layer. The projection and addition on the function f_o is performed by the neuron present at the output layer. The projected response $\hat{y}$ is the output of the neuron present in the output layer. The projected answer for the single neuron present at the output layer is:

$$\hat{y} = f_o\left[\Theta'' + \sum_{j=1}^{n_h} w''_j f_h\left(\sum_{i=1}^{n_v} w'_{ij} x_i + \Theta' \right) \right]$$

Where number of input neurons is represented by n_v, the number of hidden neurons are represented by n_h. Bias of the neurons present in the hidden layer are represented by Θ' and bias of the neurons present in the output layer is represented by Θ''. The transfer functions are horizontally shifted by them. Random values are assigned to weights and biases before calibration, these values can also be modified by learning algorithms during training process. The output value i.e. recognized y value is passed in the network through the training process. If the predicted response is different from that of experimental response then difference between them is calculated and this difference is taken as error value. This estimated error is propagated back and the parameters are adjusted so that the error is minimized. Till the error value is minimized, these two steps are repeated. These steps frame an epoch. From this it is clear that the learning algorithm always tries to minimize the error, and it will be always trying to get an acceptable low level error value.

Implementation of FFBPNN

The extracted features after applying DCT on mammogram are supplied as input to the feed-forward back propagation neural network at the input layer. Random weight and bias values are assigned and output is calculated by summation unit and transfer function sends output to the next hidden layer. For all the hidden layers this process is continued. At the output layer there is only one neuron which can classify the mammogram as benign or malignant. Then the output is compared with actual output if there is a difference between them it is calculated and treated as error. If any error is there it is calculated and it is propagated back to the last hidden layer. This NN is called Backward Propagation Neural Network, because there is propagation of delta values or error values backward. Depending on the delta value the weight and bias values are changed and process is repeated till there is no error. Once this training process is over, the next step is testing. In testing process the mammogram which needs to be tested is preprocessed, segmented and then DCT is applied and features of the segmented mammogram are extracted. These features are sent as input to the feed-forward back propagation neural network and it will classify the mammogram as either benign or malignant.

To create FFBPNN MATLAB provides a function "newff" and "sim" simulate a Simulink model. Inbuilt function "sim" compares the extracted features of the mammogram under test conditions to all the mammograms in the database, if the features are matched it displays the appropriate result to the user.

IV. SEQUENCE DIAGRAM

A sequence diagram is a representation of series of message communications between the participating members. In fig. 6 the user first loads the mammogram which is then subjected to preprocessing followed by segmentation. Features of the segmented mammogram are extracted followed by training which trains the system using FFBPNN. In the testing phase the user follows the same procedure till feature extraction then image undergoes testing and then the appropriate result is displayed to the user. Then results are analyzed by checking the training time and accuracy of the classifiers.
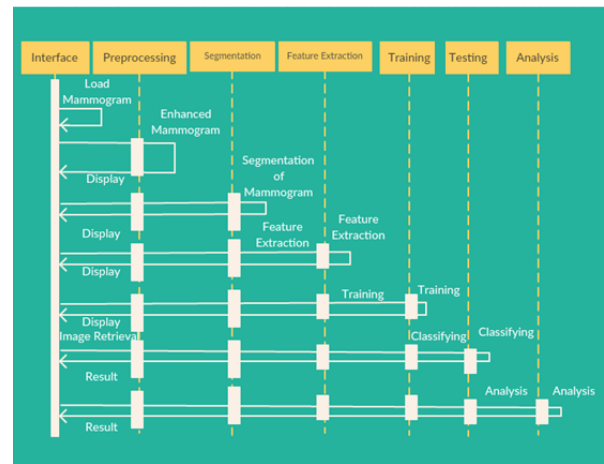

Fig. 6 Sequence diagram of the proposed system

V. RESULT ANALYSIS

We can find the accuracy of the classifier by analyzing the results. Results can be analyzed by checking True Positive, True Negative, False Positive and False Negative output values of the classifier. From the Table 1 it is clear that the proposed approach which is based on FFBPNN got a better results and classification rate of 96.66%.

Mammograms	Tested	TP	TN	FP	FN
Normal	30	29	1	0	0
Abnormal	30	29	1	0	0
Total	60	58	2	0	0

Table 1 Result analysis on different Mammograms

VI. CONCLUSION

The system takes mammogram, preprocesses it by applying Adaptive Histogram Equalization. By using K Means Clustering algorithm, enhanced image is segmented. Features of segmented mammogram are extracted. These extracted features are fed as input to the classifier Feed Forward Back Propagation Neural Network. This classifies the mammogram as benign or malignant. The proposed approach which is based on FFBPNN got a better results and classification rate of 96.66%. This will help the doctors to diagnose breast cancer and help to save the lives of many women's.

In future accuracy can be increased by using other classification methods or by extracting other features.

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