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Tumor Prediction in Mammogram using Neural Network

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Tumor Prediction in Mammogram using Neural Network

Ms. P. Valarmathi [α] & Dr. V. Radhakrishnan [σ]

Abstract - Detecting micro calcifications - early breast cancer indicators – is visually tough while recognizing malignant tumors is a highly complicated issue. Digital mammography ensures early breast cancer detection through digital mammograms locating suspicious areas with benign/-malignant micro calcifications. Early detection is vital in treatment and survival of breast cancer as there are no sure ways to prevent it. This paper presents a method of tumor prediction based on extracting features from mammogram using Gabor filter with Discrete cosine transform and classify the features using Neural Network.

Keywords : mammograms, micro calcifications, gabor filter, discrete cosine transform, artificial neural network (ANN).

I. Introduction

Digital mammography and computer aided diagnostics ensure that physicians can take accurate decisions with regard to breast cancer. There was much progress recently in the development of computer aided systems to classify mammograms. Mammograms are breast region X-ray images revealing points with high intensity density which could potentially be a tumor. Thus early diagnosis and screening is crucial for successful treatment/cure. Usually, masses and calcium deposits are identified visually as such deposits are denser than the surrounding soft tissue. Malign tumors are associated with unusually smaller clustered calcification. Other calcification types that correspond to benign tumors are diffuse, regional, segmental or linear and they are termed micro calcification.

A mammogram is done through compressing the patient's breast between two acrylic plates and passing an X-ray signal through it. It is al gray scale image indicating details inside the breast through contrast. Such details can also be normal tissues, vessels, muscles, varied masses and noise. Every mass type has varied shape, size, distribution, and brightness acting as features to help a radiologist toe diagnose breast tumors effectively.

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Mammograms with clustered micro-calcifications, mass lesions, breast architecture distortion and breast asymmetry have shown that they are linked to breast cancer. Micro calcifications are small, bright and arbitrarily shaped regions, whereas mass lesions are dense, have different size and properties and which are described as circumscribed, speculated or ill-defined [1, 2]. Circumscribed masses are usually uniform and smooth shaped like irregular circles. Speculated lesions are segments distributed as a multi armed star in many directions while ill-defined masses lack a specific pattern. Figure 1 shows examples of these features.

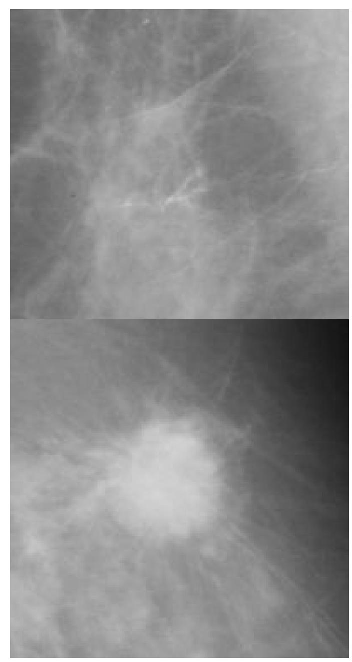

Figure 1 : Abnormal Mammograms

Currently, micro calcification detection is hard due to their fuzzy nature; low contrast and low distinguishing ability from ROS with their sizes ranging between 0.1-1.0 mm with the average being 0.3 mm. Micro calcifications shapes, distribution and size are varied. However it is hard to segment micro calcifications as they are surrounded by tissues [3]. Much research for various types of breast abnormalities was undertaken in the last two decades. Currently, computer aided mammogram detection systems for mass/micro calcification are used clinical routines like Image Checker and Second Look [4].

CAD system's general architecture includes image pre-processing, definition of region(s) of interest, features extraction and selection, and classification. Generally computer aided mammography techniques cover image enhancement, segmentation, detection and classification [4].

Various features were extracted for mammogram abnormalities. Masses feature extraction, [5] has been split into three categories, intensity features, shape features and texture features. The wavelet, fractal, statistical, and vision-models-based features are used for masses detection [1]. Cheng et al[3] summarized micro calcification detection features into individual micro calcification features, statistical texture features, multi-scale texture features and fractal dimension features. Classification methods classify suspicious mammogram areas into benign, malignant or normal tissue. Digital mammograms present classification techniques are common and similar to classification procedures in neural networks, Bayesian belief network, and K-nearest neighbor. Though it was demonstrated that both LDA and ANN (artificial neural network) classify masses well [5].

Image feature extraction is important in signal processing techniques preprocessing. Digital image features can be extracted directly from spatial data or from another space. Using a different space through special data transform like Fourier transform or wavelets transform could separate special data with specific characteristics. Detecting image texture features is difficult as such features are variable and scale-dependent.

An uncorrelated measurement should be investigated to transform the data into a different domain in designing an automated mammogram classifier. Mammogram classification requires a transform that uncorrelated data without losing the main characteristics of the image. Naturally discrete wavelets transform suit mammogram feature extraction. The idea of wavelets is explained by Daubechies (1992) [6] who said that wavelets are functions used to prevent other functions. This is called mother wavelet. A set of functions is generated by mother function translations and dilations.

Wavelet decomposition is through 2D wavelets transform application to an image producing a set of four different coefficients in every decomposition level. Three levels of 2D wavelets decomposition are illustrated in Figure 2 [7]. The produced coefficients are

- Low frequency coefficients (A).
- Vertical high frequency coefficients (V).
- Horizontal high frequency coefficients (H).
- High frequency coefficients in both directions (D).

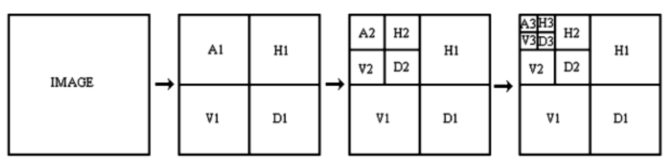

Figure 2 : Wavelets multi resolution decomposition

In this paper, the classification accuracy achieved for mammograms using Multi-Layer Perception Neural Network (MLPNN) is investigated. For predicting tumor, features are extracted from mammogram using Gabor filter with Discrete Cosine Transform (DCT). The rest of the paper is organized as follows: Section 2 reviews some the researches available in the literature; section 3 details the various techniques used in this study, section 4 reports the results and section 5 concludes the paper.

II. Related Works

Buciu et al [8] suggested an approach to deal with digital mammogram classification. Patches around tumors are manually extracted to segment abnormal areas from the rest of the image, considered as background. Gabor wavelets filter mammogram images and directional features extracted at various orientations/frequencies. Principal Component Analysis reduces filtered/unfiltered high-dimensional data dimensions. Proximal Support Vector Machines finally classify data. Superior mammogram image classification performance is attained after Gabor features extraction instead of using original mammogram images. Gabor features robustness for digital mammogram images distorted by Poisson noise of differing intensity levels is also addressed.

Eltoukhy, et al., [9] described a wavelet and curve let transform comparative study for breast cancer diagnosis. Mammogram images are decomposed into various resolution levels sensitive to various frequency bands through the use of multi-resolution analysis. A set of large coefficients is extracted from each decomposition level. Then based on Euclidian distance a supervised classifier system development is undertaken. Classifier performance is evaluated through a 2 X 5-fold cross validation, followed by a statistical analysis. The experiment's results reveal that curve let transform has a higher-throughput than wavelet transform with statistically significant difference.

Suganti et al [10] presented an automated system for breast tumor classification as either malign or benign. It includes three stages: image enhancement and demising, multiple feature extraction techniques, and final classification stage. Three different classification schemes like ANNs, Support vector machines (SVMs) and Radial Basis Function (RBF) were used. The system was implemented and tested on classifier fusion techniques based on Majority Voting Methods and Behavior-Knowledge Space Method. Also SVMs were used for the first time for cluster characterization. Classifier performance was evaluated by using Receiver Operating Characteristic (ROC) methodology and classification rate. Results obtained results show high classification performance and so this method is quite promising.

Ayer et al. [11] revisited ANN models use in breast cancer risk estimation assessing both discrimination and calibration. Risk prediction was obtained using 10-fold cross-validation on a large data set of 62,219 consecutive mammography findings. ANN model achieved an AZ of 0.965, significantly higher than that of radiologists, 0.939 ($P<0.001$). ANN calibration assessed by Hosmer-Lemeshow (H-L) goodness-of-fit statistic test was 12.46 ($P>0.1$, $df=8$), indicating a good match between risk estimates and malignancy prevalence.

Islam et al [12] presented a computer aided mass classification method in digitized mammograms using Artificial Neural Network (ANN) and performing benign-malignant classification on region of interest (ROI) having mass. A major mass classification mammographic characteristic is texture. ANN exploits this to classify mass as benign or malignant. Statistical textural features in characterizing masses are mean, standard deviation, entropy, sleekness, kurtosis and uniformity. This method aims to increase classification process efficiency objectively to reduce many false-positive of malignancies. Three layers artificial neural network (ANN) with seven features was proposed to classify marked regions into benign or malignant achieving 90.91% sensitivity and 83.87% specificity which is promising compared to a radiologist's 75% sensitivity.

Cede no. [13] suggested improvements in neural network training for pattern classification with the proposed training algorithm being inspired by neuron's biological met plasticity property and Shannon's information theory. During training the Artificial metaplasticity Multilayer Perceptron (AMMLP) algorithm prioritizes updating weights for less frequent activations over those more frequent. This way metaplasticity is modeled arficially. AMMLP achieves better efficient training maintaining MLP performance. Wisconsin Breast Cancer Database (WBCD) is used to test the proposed algorithm. AMMLP performance is tested through classification accuracy, sensitivity and specificity analysis, and confusion matrix. AMMLP's 99.26% classification accuracy is promising compared to back propagation Algorithm (BPA) and recent classification techniques when applied to the same database.

Karabatak et al [14] presented an automatic diagnosis system to detect breast cancer based on association rules (AR) and neural network (NN). AR reduces breast cancer database dimensions in this study with NN being used for intelligent classfication. AR + NN system performance is compared with NN model with input feature dimension being reduced from nine to four through the use of AR. A 3-fold cross validation method was applied to Wisconsin breast cancer database to evaluate system performance in test stage. The proposed system's correct classification rate is 95.6% proving that AR could reduce feature space dimensions and that the AR + NN model can provide quick automatic diagnosis for other diseases

III. Material and Methods

a) Mammogram Database

Mammogram images used in experiments were from the Mammographic Image Analysis Society (MIAS) [15] and the 322 samples database was labeled as one of the three categories: normal, benign and malign. There are 208 normal images, 63 benign and 51 malign. Each 1024×1024 pixels image is centered. Abnormal cases are divided into six categories: micro calcification, circumscribed masses, speculated masses, ill-defined masses, architectural distortion and asymmetry. Coordinates of abnormality center are provided along with approximate radius (in pixels) of a circle enclosing abnormality for every abnormal case. The widest identified abnormality has a radius of 197 pixels, while tightest abnormality has a 3 pixel radius.

b) Gabor Wavelets

2D Gabor wavelets were much used in computer vision applications to model biological-like vision systems. Studies reveal that Gabor elementary functions suit modeling simple cells in visual cortex [16]. Other property is provided by optimal joint resolution in both space and frequency, suggesting simultaneous analysis in both domains. Gabor wavelet orientation property suits it for several applications, including image texture analysis or image retrieval [17]. A complex Gabor wavelet is a product of a Gaussian kernel with a complex sinusoid described as:

$$\psi_k(z)=\frac{k^T k}{\sigma^2}\exp\left(\frac{k^T k}{2\sigma^2}z^T z\right)\left(\exp\left(ik^T z\right)-\exp\left(-\frac{\sigma^2}{2}\right)\right)$$

where k and F_{PCA}^{kc} are characteristic wave vector:

$$k_v=2^{-\frac{v+2}{2}}\pi,\ \ 1ex\varphi_\mu=\mu\frac{\pi}{8}$$

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The parameters ν and μdefine a filter's frequency and orientation. Given an image I (z), a 2D Gabor wavelet transform is a convolution of this image I (z) with a family of Gabor filters and many orientation and frequency values:

$$I_k(z) = \iint I(z')\psi_k(z - z')dz'$$

c) Discrete Cosine Transform

Orthogonal transforms are used in pattern recognition as it enables a noninvertible transformation from the pattern space to a reduced dimensionality feature space [18]. Thus, classification procedures are carried out with fewer features albeit with a small increase in classification error. Discrete Cosine Transform (DCT) converts time series signal into basic frequency components. On application of DCT an image is decomposed into a set of cosine basis functions. The DCT [19] of a list of n real numbers s(x), x = 0,..., n-1, is the list of length n given by:

$$S(u) = \sqrt{2/n}C(u)\sum_{x=0}^{n-1} s(x)\cos\frac{(2x+1)u\pi}{2n}$$

where $C(u) = 2^{-1/2}$ for u=0 or otherwise $C(u) = 1.$

The constant factors are chosen so that the basis vectors are orthogonal and normalized.

The inverse cosine transform (IDCT) is computed as follows:

$$S(x) = \sqrt{2/n}\sum_{x=0}^{n-1} C(u)s(u)\cos\frac{(2x+1)u\pi}{2n}$$

Where $C(u) = 2^{-1/2}$ for u=0 or otherwise $C(u) = 1.$

d) Artificial Neural Network (ANN)

Artificial Neural Network (ANN)are a collection of mathematical models imitating properties of biological nervous systems and functions of adaptive biological learning, made up of many processing elements highly interconnected with weighted links being similar to synapses. Unlike linear discriminates, ANNs use non-linear mapping functions as decision boundaries. ANN's advantage is their ability to self-learn, and often solve issues too complex for traditional techniques, or hard to find algorithmic solutions.

It includes input and output layers with one or more hidden layers between them. Depending on weight values of w(j, i) and w(k, j), inputs are r amplified/weakened to get a solution correctly. Determined weights train ANN using known samples. Generally, a known mammogram database with chosen features and desired results trains the ANN. After weights determination ANN can readily classify masses.

ANNs are computer models inspired by biologic neural network structures, consisting of interconnected nodes with their overall ability to predict outcomes being determined by intra neuron connections [20]. ANNs simulate neural processes by summing negative (inhibitory) and positive (excitatory) inputs to produce a single output [21]. Though ANNs differ in how neurons are connected and inputs processed, the focus is on "feedforward" networks, a commonly used ANN model in medical research.

Figure 3 illustrates ANN's generic structure consisting of node series in three layers (input, hidden, and output layers). Each input layer node is called an input node and represents an input variable (eg, an imaging feature like calcification/breast density) used as an outcome predictor. Output layer's single node (output node) represents predicted outcome (eg, malignancy probability). An inputs and output correspond to predictor variables and the outcome variable Y, respectively, in logistic regression models. Hidden layer nodes (hidden nodes) have intermediate values calculated by networks without any physical meaning. Hidden nodes allow ANN to model complex relationships between input variables and outcome.

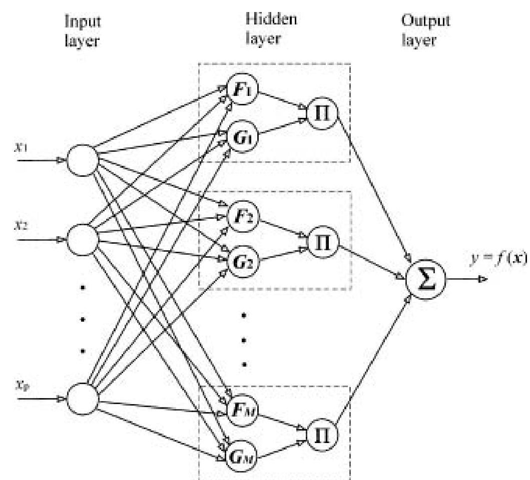

Figure 3 : Generic Structure of Artificial Neural Network

Different layer nodes are connected through connection weights, represented by arcs, containing "knowledge" representing relationships between variables, corresponding to coefficients in a logistic regression model. ANNs "learn" relationships between input variables and effects they have on outcome by strengthening (increasing) or weakening (decreasing) connection weight values through known cases basis. The optimal weight estimation process generating reliable outcomes is called learning/ training [22]. Many algorithms can train ANNs and the most popular is back propagation which in turn is based on the idea of adjusting connection weights to minimize discrepancy between real and predicted outcomes by propagating discrepancy in a backward direction (ie, from output node to input nodes). Table 1 gives the parameters of the ANN used in this study.

Table 1 : Parameters of the ANN

Number of input nodes	25
Number of outputs	2
Number of hidden layer	1
Number of neurons in hidden layer	10
Learning Algorithm	Back propagation algorithm
Learning rate	0.1
Momentum	0.5
Activation function	sigmoid /tanh/gaussian

IV. Results and Discussion

The performance efficiency of the ANN for different activation function for classifying the mammograms is investigated. The mammograms were classified as micro calcified and non-micro calcified. Features are extracted from the mammograms using Gabor filter with DCT. Mini MIAS containing 61 mammograms was used for evaluation. The following Table 2 shows the summary.

Table 2

	Naïve Bayes	Neural Network		
		Sigmoid Activation	Tanh Activation	Gaussian Activation
Correctly Classified Instances	38	55	56	58
Incorrectly Classified Instances	23	6	5	3
Kappa statistic	0.2549	0.8034	0.8359	0.9019
Mean absolute error	0.3692	0.14	0.1135	0.0874
Root mean squared error	0.5903	0.3098	0.277	0.2233
Relative absolute error	73.93%	28.03%	22.72%	17.50%
Root relative squared error	118.06%	61.96%	55.40%	44.66%
Coverage of cases (0.95 level)	70.49%	91.80%	95.08%	95.08%
Mean rel. region size	56.56%	68.85%	67.21%	68.85%
Total Number of Instances	61	61	61	61

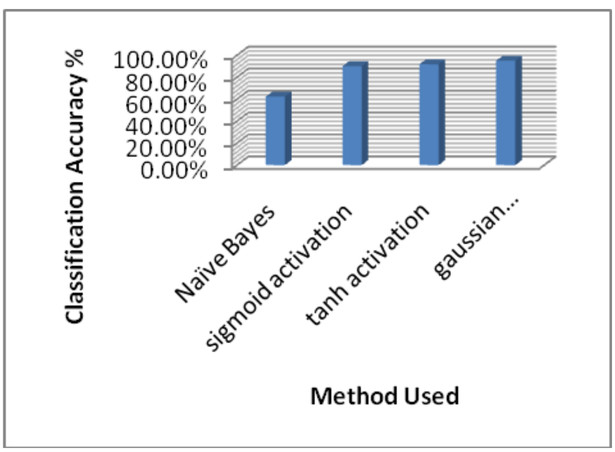

Figure 4 : Classification Accuracy Obtained by Various Activation Function

It is observed from Figure 4 that the ANN with Gaussian function achieves the maximum classification accuracy of 95.08%. Similarly, the RMSE is also the lowest for Gaussian function. Table 3 tabulates the precision, recall and f-measure of various methods. Figure 5 shows the graph of precision and recall.

Table 3 : Precision, Recall and F-Measure

	Precision	Recall	F-Measure
Naïve Bayes	0.64	0.623	0.617
Sigmoid Activation	0.904	0.902	0.902
Tanh Activation	0.919	0.918	0.918
Gaussian Activation	0.955	0.951	0.951

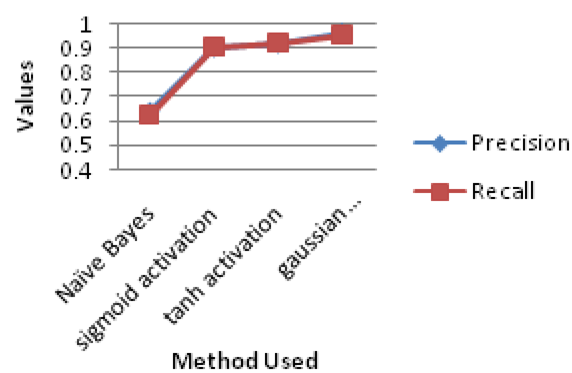

Figure 5 : Precision and Recall

The best precision and recall was achieved for ANN with Gaussian function.

V. Conclusion

Computer aided mammography was extensively studied. This research is mainly to detect and classify masses and micro calcifications. Techniques in computer-aided mammography include pre-processing, segmenting suspicious areas, extracting features, and classifying into benign, malignant or normal tissue. Different techniques-/algorithms were proposed or extended for digital mammograms, but reliable masses or micro calcification detection continues to be a challenge. This paper presents a method of tumor prediction based on extracting features from mammogram using Gabor filter with Discrete cosine transform and classify the features using Neural Network. The efficiency of various activation functions for ANN is also investigated. Experimental results show that the Gaussian function achieves the best performance for classification.

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