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A Review of Breast Cancer Detection using ART Model of Neural Networks

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Abstract: ***Artificial neural networks have featured in a wide range of medical journals, often with promising results. This paper reports on a systematic review that was conducted to assess the benefit of artificial neural networks (ANNs) as decision making tools in the field of cancer. The number of clinical trials (CTs) and randomised controlled trials (RCTs) involving the use of ANNs in diagnosis and prognosis increased from 1 to 38 in the last decade. However, out of 396 studies involving the use of ANNs in cancer, only 27 were either CTs or RCTs. Neural Networks are currently a 'hot' research area in medicine, particularly in the fields of radiology, urology, cardiology, oncology and etc. The main aim of research in medical diagnostics is to develop more cost-effective and easy–to-use systems, procedures and methods for supporting clinicians. Breast cancer diagnosis has been approached by various machine learning techniques for many years. This paper presents a review on classification of Breast cancer using Adaptive Resonance Neural Networks (ARNN), ART, and Feed Forward Artificial Neural Networks. The performance of the network is evaluated using Wisconsin breast cancer data set for various training algorithms.***

Keywords— Artificial neural networks; Breast Cancer; ARNN; ART; Medical decision making;

1. INTRODUCTION

The breast cancer diagnosis problem has attracted many researchers in computational intelligence, data mining, and statistical fields. Breast cancer [1] is cancer of breast issue. Breast cancer is a malignant tumor that has developed from cells of the breast. Breast cancer has become a major cause of death among women in developed countries [2]. The most effective way to reduce breast cancer deaths is detect it earlier. However earlier treatment requires the ability to detect breast cancer in early stages. Early diagnosis requires an accurate and reliable diagnosis procedure that allows physicians to distinguish benign breast tumors from malignant ones. The automatic diagnosis of breast cancer is an important, real-world medical problem [3]. Thus, finding an accurate and effective diagnosis method is very important. In recent years machine learning methods have been widely used in prediction, especially in medical diagnosis. Medical diagnosis is one of major problem in medical application. Several research groups are working world wide on the development of neural networks in medical diagnosis. Neural networks are used to increase the accuracy and objectivity of medical diagnosis. 'Neural networks' research and application have been studied for a half of hundred years. Artificial neural networks (ANNs) [4, 5] have been recently proposed as a very effective method for pattern recognition, machine learning and data mining. The published literature suggest s that ANN models have been shown to be valuable tools in reducing the workload on the clinicians by detecting artifact and providing decision support, potentially with the ability to automatically reestimate the model on-line. However, there are relatively few published clinical trials, and even fewer testing the clinical value of ANNs against established linear-in-the-parameters statistical methods (Lisboa, 2002). There are two recurring concerns on ANNs. The first is the use of first principle statistical methods to control model complexity, which has been addressed by regularization methods and with the use of cross-validation (Biganzoli, Boracchi, Mariani, & Marubini, 1998; Lisboa, Wong, Harris, & Swindell, 2003; Ripley, 1996; Ripley & Ripley, 2001). The second key issue is transparency, i.e. explaining what influences the network predictions and how to resolve outcome predictions in terms of readily understood clinical statements. This paper describes neural network approaches to breast cancer diagnosis. Neural networks have been widely used for breast cancer diagnosis. However, most of these applications assumed a predefined network architecture (including connectivity and node transfer functions) and used a training algorithm.

The remainder of this paper is organized as follows. Section 2 describes the framework architecture of neural network and Section 3 describes the framework of ART. The related work in section 4 provides an overview of neural network approaches to breast cancer diagnosis. Finally, the conclusions and future work section conclude the paper and outlines the future work.

2. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANN) [5] have been developed as generalizations of mathematical models of biological nervous systems. A first wave of interest in neural networks (also known as connectionist models or parallel distributed processing) emerged after the introduction of simplified neurons by McCulloch and Pitts (1943).

The basic processing elements of neural networks are called artificial neurons, or simply neurons or nodes. In a simplified mathematical model of the neuron, the effects of the synapses are represented by connection weights that modulate the effect of the associated input signals, and the nonlinear characteristic exhibited by neurons is represented by a transfer function. The neuron impulse is then computed as the weighted sum of the input signals, transformed by the transfer function. The learning capability of an artificial neuron is achieved by adjusting the weights in accordance to the chosen learning algorithm.

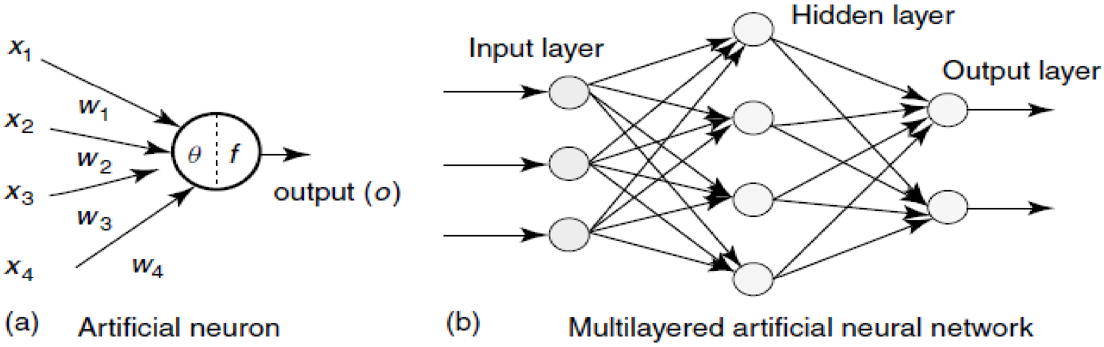


Figure 1: Architecture of an Artificial Neuron and a Multilayered Neural Network

A typical artificial neuron and the modeling of a multilayered neural network are illustrated in Figure 2. Referring to Figure 2, the signal flow from inputs x1. . . xn is considered to be unidirectional, which are indicated by arrows, as is a neuron's output signal flow (O). The neuron output signal O is given by the following relationship:

$$O = f(net) = f(\sum_{j=1}^{n} w_j x_j \qquad (1)$$

where wj is the weight vector, and the function f(net) is referred to as an activation (transfer) function. The variable net is defined as a scalar product of the weight and input vectors,

$$net = w^T x = w_1 x_1 + \cdots + w_n x_n \qquad (2)$$

where T is the transpose of a matrix, and, in the simplest case, the output value O is computed as

$$O = f(net) = \begin{cases} 1 \; if \; w^T x \geq \theta \\ 0 \; otherwise \end{cases} \qquad (3)$$

where θ is called the threshold level; and this type of node is called a linear threshold unit.

3. ADAPTIVE RESONANCE THEORY

3.1Adaptive Resonance Theory (ART) [6,7] is a theory developed by Stephen Grossberg and Gail Carpenter on aspects of how the brain processes information. It describes a number of neural network models which use supervised and unsupervised learning methods, and address problems such as pattern recognition and prediction.

The primary intuition behind the ART model is that object identification and recognition generally occur as a result of the interaction of 'top-down' observer expectations with 'bottom-up' sensory information. The model postulates that 'top-down' expectations take the form of a memory template or prototype that is then compared with the actual features of an object as detected by the senses. This comparison gives rise to a measure of category belongingness. As long as this difference between sensation and expectation does not exceed a set threshold called the 'vigilance parameter', the sensed object will be considered a member of the expected class.

3.2 Types of ART

3.2.1 ART 1 is the simplest variety of ART networks, accepting only binary inputs.

3.2.2 ART 2 extends network capabilities to support continuous inputs.

3.2.3 ART 2-A is a streamlined form of ART-2 with a drastically accelerated runtime, and with qualitative results being only rarely inferior to the full ART-2 implementation.

3.2.4 ART 3 builds on ART-2 by simulating rudimentary neurotransmitter regulation of synaptic activity by incorporating simulated sodium (Na+) and calcium (Ca2+) ion concentrations into the system's equations, which results in a more physiologically realistic means of partially inhibiting categories that trigger mismatch resets.

3.2.5 Fuzzy ART implements fuzzy logic into ART's pattern recognition, thus enhancing generalizability. An optional (and very useful) feature of fuzzy ART is complement coding, a means of incorporating the absence of features into pattern classifications, which goes a long way towards preventing inefficient and unnecessary category proliferation.

3.3 Basic features of ART systems

The basic features of Adaptive Resonance Theory [8] and its relation to perception are layed out in a great number of articles by Grossberg and his associates (see for example Grossberg 1986 for an overview). A block diagram for a typical ART system is displayed in figure 2. The main components are the attentional subsystem and the orienting subsystem. The attentional subsytem consists, among others, of two fields of neurons, F1 and F2, where each field may consist of several layers of neurons. These fields are connected with feedforward and feedback connection weights. The name short term memory (STM) will be associated with the pattern of activity that develops on a field as an input pattern is processed. The orienting subsystem is necessary to stabilize the processing of STM and the learning in LTM. As can be seen from the figure, the F1 field receives input from possibly three sources. These three input sources are the bottom-up input to F1, the top-down input from F2 and the gain control signal. To avoid the possibility that mere feedback from F2 can generate spontaneous activity at level F1, i.e., to avoid that the system hallucinates, system dynamics are limited in such a way that at least two out of three inputs must be active to generate activity at the F1 field. This is called the 2/3 rule in ART. The same rule applies to the three possible input sources for the F2 level

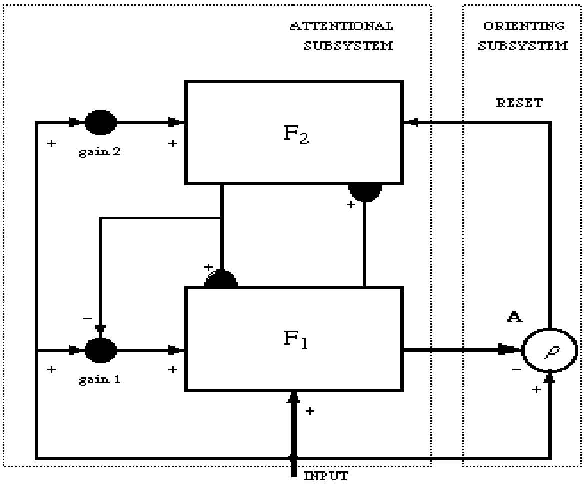
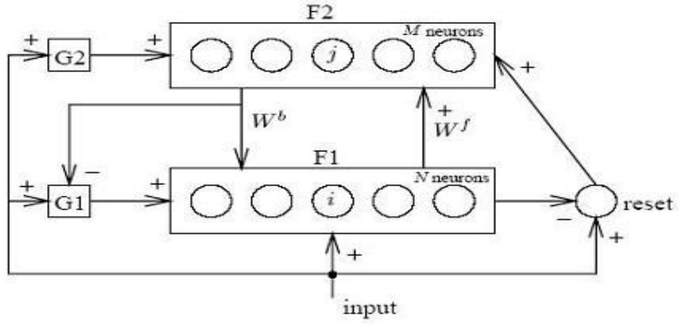


Figure 2. Typical ART neural network block diagram.

After preprocessing, the input activity pattern is transformed to the first field F1. Field F1 is connected to field F2 with feed forward and feedback connections which are indicated with black half ellipses. These connections form the long term memory components of this system. All ART systems incorporate basic features, notably, pattern matching between bottum-up input and top-down learned prototype vectors. This matching leads either to a resonant state that focusses attention and triggers stable prototype learning or to a self-regulating parallel memory search. This search ends in either of two ways. First, if an established category is selected, then this prototype may be refined to incorporate new information in the input pattern. In this case when an input matches an established category, we speak of resonance. This resonant state persists long enough for learning to occur; hence the term adaptive resonance theory. Second, if the search ends by selecting a previously untrained node, then learning of a new category takes place. The criterion of an acceptable match is defined by a dimensionless parameter called vigilance. Vigilance weighs how close an input must be to the top-down prototype for resonance to occur. Because the vigilance parameter can vary across learning trials a single ART system is able to encode widely differing degrees of generalization. Low vigilance leads to broad generalization and more abstract prototypes than high vigilance. In the limit of very high vigilance, prototype learning reduces to exemplar learning.

3.4 ART1: The simplified neural network model

The ART1 simplified model consists of two layers of binary neurons (with values 1 and 0), called F1 (the comparison layer) and F2 (the recognition layer). Each neuron in F1 is connected to all neurons in F2 via the continuous-valued forward long term memory (LTM) Wf , and vice versa via the binary-valued backward LTM Wb. The other modules are gain 1 and 2 (G1 and G2), and a reset module. Each neuron in the comparison layer receives three inputs: a component of the input pattern, a component of the feedback pattern, and a gain G1. A neuron outputs a 1 if and only if at least three of these inputs are high: the 'two-thirds rule.' The neurons in the recognition layer each compute the inner product of their incoming (continuous-valued) weights and the pattern sent over these connections. The winning neuron then inhibits all the other neurons via lateral inhibition. Gain 2 is the logical 'or' of all the elements in the input pattern x. Gain 1 equals gain 2, except when the feedback pattern from F2 contains any 1; then it is forced to zero. Finally, the reset signal is sent to the active neuron in F2 if the input vector x and the output of F1 by more than some vigilance level.



The ART1 neural network.

Operation

The network starts by clamping the input at F1. Because the output of F2 is zero, G1 and G2 are both on and the output of F1 matches its input. The pattern is sent to F2, and in F2 one neuron becomes active. This signal is then sent back over the backward LTM, which reproduces a binary pattern at F1. Gain 1 is inhibited, and only the neurons in F1 which receive a 'one' from both x and F2 remain active. If there is a substantial mismatch between the two patterns, the reset signal will inhibit the neuron in F2 and the process is repeated.

1. Initialisation:

$$w_{ji}{}^{b}(0) = 1$$
$$w_{ij}{}^{f}(0) = \frac{1}{1+N}$$

where N is the number of neurons in F1, M the number of neurons in F2, 0 i < N, and $0 \le j < M$. Also, choose the vigilance threshold ρ, $0 \le \rho \le 1$;

2. Apply the new input pattern x:

$$y_i{}' = \sum_{j=1}^{N} w_{ij}{}^{f}(t)\, x_i;$$

3. Compute the activation values y0 of the neurons in F2:
4. Select the winning neuron k ($0 \le k < M$):
5. Vigilance test: if

$$\frac{\mathbf{w}_k{}^{b}(t) \cdot \mathbf{x}}{\mathbf{x} \cdot \mathbf{x}} > \rho,$$

where . denotes inner product, go to step 7, else go to step 6. Note that $\mathbf{w}_k{}^{b} \cdot \mathbf{x}$ essentially is the inner product $\mathbf{x}^{*} \cdot \mathbf{x}$,which will be large if $\mathbf{x}^{*}$ and $\mathbf{x}$ near to each other;

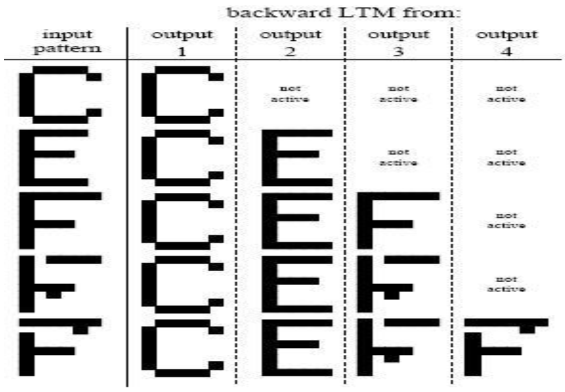
6. Neuron k is disabled from further activity. Go to step 3;
7. Set for all l, $0 \le l < N$:

$$w_{kl}{}^{b}(t+1) = w_{kl}{}^{b}(t)\, x_l,$$
$$w_{lk}{}^{f}(t+1) = \frac{w_{kl}{}^{b}(t)\, x_l}{\frac{1}{2} + \sum_{i=1}^{N} w_{ki}{}^{b}(t)\, x_i};$$

8. Re-enable all neurons in F2 and go to step 2.

An example of the behaviour of the Carpenter Grossberg network for letter patterns. The binary input patterns on the left were applied sequentially. On the right the stored patterns (i.e., the weights of Wb for the first four output units) are shown.

An example of ART 1



4. LITRATURE SURVEY

Literature survey reveals that different algorithms for artificial neural networks in medical system, computer aided diagnosis system and Brest cancer [9, 10] have been suggested and developed. For the sake of comparison, it is very difficult to get a result as of which system is better one as it depends upon many factors like number of cases to be examined, type of abnormalities and database being used.

In 2001, Garvican and Field [11] evaluated the performance of a commercial CAD system with prior mammograms of interval- cancer cases; the system was able to detect normal areas and was not efficient in detecting cancer in the difficult cases analyzed.

In 2001, Moberg et al. [12] conducted a study on CAD-assisted analysis of cases of interval cancer and found that the system had no effect on the sensitivity or the specificity of the radiologists.

In 2001, P.J.G. Lisboa [13]" evidence of health benefit from artificial neural networks in medical intervention" This review shows that artificial neural networks have been alongside the bootstrap, Bayesian modelling using Gibbs sampling, generalised additive models and CART as new trends in medical statistics.

In 2002, Evans et al. [14] investigated the performance of a commercial CAD system in detecting invasive lobular arcinoma of the breast, and reported a sensitivity of 91% with screening mammograms demonstrating biopsy-proven cancer, and 77% with the corresponding prior mammograms.

In 2002, Ikeda et al. [15] evaluated the performance of a commercial CAD system using prior mammograms of 172 cases of cancer with subtle findings and reported a detection sensitivity of 42%.

In 2003,Sumkin et al. [16] found that the sensitivity was not affected significantly by the availability of prior mammograms, but the specificity was improved.

In 2003, Debra M. Ikeda, MD et al. [17] "Evaluate, by using a computer-aided detection (CAD) program, the nonspecific findings on normal screening mammograms obtained in women in whom breast cancer was later detected at follow-up screening mammography."

In 2003, Alberta [18] Program for the Early Detection of Breast Cancer. Ethics approval for the study was obtained from the Conjoint Health Research Ethics Board, Office of Medical Bioethics, University of Calgary, and the Calgary Regional Health Authority. The film mammograms were digitized at the spatial resolution of 50 m and gray-scale resolution of 12 bits per pixel using the Lumiscan 85 laser scanner (Lumisys, Sunnyvale, CA).

In 2003, Matsurba et al. [19] developed the notion for identification of architectural distortion existing around skin line and within mammary glandular tissues. To detect the suspected areas, top hat processing was performed. The technique was tested on 17 cases with focal retraction and was quite effective to detect architectural distortion.

In 2004, Ichikawa et al. [20] developed an automatic method for detecting areas of architectural distortion with Spiculation. The distorted areas are detected by concentration indexes of line-structures extracted by using mean curvature. After that, discrimination analysis of nine features is employed for the classifications of true and false positives. The employed features are the size, the mean pixel value, the mean concentration index, the mean isotropic index, the contrast, and four other features based on the power spectrum. The accuracy of the classification was 76% and the sensitivity was 80% with 0.9 false positives per image in our database in regard to Spiculation. Although method was effective in detecting the area of architectural distortion yet, some architectural distortions were not detected accurately because of the size, the density, or the different appearance of the distorted areas.

In 2004, Rafael et al. [21] "Radial basis function" This study shows that the RBF-Simulated Annealing classifier, is more time consuming for training the network than the other methods studied.

In 2005, Paulo J. Lisboa, Azzam F.G. Taktak [22] "This paper reports on a systematic review that was conducted to assess the benefit of artificial neural networks (ANNs) as decision making tools in the field of cancer" The conclusion from this is that a review of PubMed listed publications involving clinical trials of neural network systems identified trends in areas of clinical promise, specifically in the diagnosis, prognosis and therapeutic guidance for cancer, but also the need for more extensive application of rigorous methodologies.

In 2005, Varela et al. [23] showed that the accuracy of classification between benign and malignant masses could be increased by using prior mammograms as reference.

In 2006, A.Punitha, et al. [24] "A combination of genetic algorithm and ART neural network for breast cancer diagnosis" This study explored the possibility of combining the features of genetic algorithmsand neural network to classify the breast cancer.

In 2006, Eltonsy et al. [25] described a method for tracing out the architectural distortion based on the identification of points surrounded by concentric layers of image activity. The sensitivity was found to be 91.3% with 9.1 false positive per image.

In 2007, Rashed et al. [26] proposed an effective supervised classifier using the discrete wavelet transform. They have discussed that in some cases there were no suitable difference in shape between benign and malignant lesion and it could be identified only through biopsy. Since the texture of mammogram is an irregular texture therefore features like entropy, energy, contrast and homogenous nature could be improved when texture is combined with multi resolution transform. Speculated lesions were classified better than circumscribed lesion, micro calcifications, and normal tissues. But there was no fixed range that could be detected for ill defined lesion.

In 2007, Kunio Doi [27] "In this article, the motivation and philosophy for early development of CAD schemes are presented together with the current status and future potential of CAD in a PACS environment" It shows that in the future, it is likely that CAD schemes will be incorporated into PACS, and that they will be assembled as a package for detection of lesions and also for differential diagnosis.

In 2008, Shantanu et al. [28] "Detection of Architectural Distortion in Prior Mammograms of Interval-cancer Cases with Neural Networks" The results indicate that the proposed methods can be used to achieve earlier detection of subtle signs of breast cancer in mammograms, in particular architectural distortion, with good accuracy.

In 2009, Banik et al. [29] introduced the concept of prior mammograms where the screening mammogram was obtained in the visit prior to that when breast cancer was detected. The author used estimated Fractal dimension of each ROI. The FROC (Free receiver operating characteristics) analysis done with a set of four features including fractal dimension, entropy, sum entropy and inverse difference moment provided a sensitivity of 79% with 8.9 false positive per image.

In 2010, Mary S. Newell [30] "Screening mammography can detect breast cancer before it becomes clinically apparent. However, the screening process identifies many false-positive findings for each cancer eventually confirmed"

In 2011, F.Paulin, A.Santhakumaran [10] "This paper presents a study on classification of Breast cancer using Feed Forward Artificial Neural Networks. Back propagation algorithm is used to train this network. The performance of the network is evaluated using Wisconsin breast cancer data set for various training algorithms".

In 2011, Shantanu Banik, et al. [28] "Hypothesizing that screening mammograms obtained prior to the detection of cancer could contain subtle signs of early stages of breast cancer, in particular, architectural distortion" The results obtained in the present study on the automatic detection of architectural distortion in prior mammograms of interval-cancer cases are important and indicate that Gabor filters, phase portraits, fractal analysis, the angular spread of power, and structural as well as statistical texture features can be used to achieve the detection of subtle signs of early stages of breast cancer in mammograms.

In 2011, Banik et al. [31] traced out the detection of architectural distortion, in mammograms of interval-cancer cases taken prior to the diagnosis of breast cancer, using Gabor filters, phase portrait analysis, fractal dimension, and texture analysis. For each ROI, the fractal dimension and Haralick texture features were computed. Analysis of the performance of the methods with free-response receiver operating characteristics indicated a sensitivity of 0.80 at 10.5 false positives per image.

In 2012, Amit Kamra et al. [32] "A Review Towards the Detection of Architecture Distortion in Mammograms" Since the scope of this review paper is focused on detection of subtle signs, only CAD techniques used for detection of architectural distortion is discussed. The vast amount of research related to analysis of mammography, as well as widespread interest from the medical community stimulates the development of for new CAD systems.

CONCLUSION

The automatic diagnosis of Brest cancer is an important, real-world medical problem. Brest cancer is one of the most common and deadly diseases in the world. Detection of Brest cancer in its early stage is the key of its cure. In this paper the author has shown how neural networks are used ART Model in actual clinical diagnosis of Brest cancer . ART model, a diagnostic system that performs at an accuracy level is constructed here. In this work, the performance of neural network with ART structure was investigated for Brest cancer diagnosis problem.

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