A NEURO-FUZZY INFERENCE MODEL FOR BREAST CANCER RECOGNITION

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ABSTRACT

Breast cancer is known as one of the most common cancers to afflict the female population. Computer assisted diagnosis can be helpful for doctors in detection and diagnosing of potential abnormalities. Several techniques can be useful for accomplishing this task. This paper outlines an approach for recognizing breast cancer diagnosis using neuro-fuzzy inference technique namely ANFIS (Adaptative Neuro-Fuzzy Inference System). Wisconsin breast cancer diagnosis (WBCD)database developed at University of California, Irvine (UCI) is used to evaluate this method. Results show that the best performances are obtained by our model compared to others cited in literatur (an accuracy of 98, 25 %).

KEYWORDS

Artificial Neural Networks, Breast Cancer, fuzzy logic, neuro-fuzzy, computer assisted diagnostic WBCD, Artificial Intelligence

1. INTRODUCTION

In [5] , breast cancer has been one of the major causes of death among women and a true emergency for the healthcare systems of industrialized countries . It is the second leading cause of cancer deaths among women in the world [2]**.**It is characterized by an abnormal multiplication of a cell in the human body. Not entailing serious consequences, early, cancer can be developed into a serious condition if treatment is not done on time. Due to its late diagnosis, it often causes a mutilating and expensive treatments accompanied by a high mortality rate. It has the form of lumps or tumors in the tissues of the breast. Tumors can either be malignant or benign. However, differentiating a malignant tumor from a benign one is a very tedious task due to the structural similarities between the two (**figure 1**) [24]

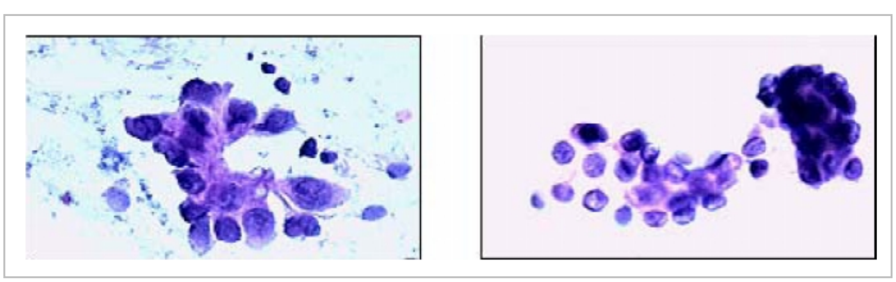


Figure 1: Fine Needle Biopsies of Breast. Malignant (left) And benign (right) breast tumors [33]

It is an extremely critical and time consuming task for the physician to accurately identify the structural differences.The question remains if there could be an automated technique that could relieve the physician of the tedious task of distinguishing a malignant tumor from a benign one [24**].** Computer aided diagnosis systems are important for pattern recognition , aiming to assist doctors in making diagnosis decisions. Machine learning have been successfully applied in computer-aided diagnosis (CAD) systems **[**7**], [**34**], [**25]**.** These methods learn hypotheses from a large amount of diagnosed samples, i.e., the data collected from a number of necessary medical examinations along with the corresponding diagnoses made by medical experts, to assist the medical experts in making a diagnosis in the future [13]

In the literature, several methods have been applied to detect the presence of cancer in the breast. Most work reported employs Neural Networks , Genetic Algorithm (GA) , Fuzzy Inference System (FIS) and Neuro-Fuzzy Hybrid Models for breast cancer classification. Some literature works based on WBCD (Wisconsin breast cancer diagnosis) are shown in the following **Table1**:

TABLE 1: Some Literature Works

References	**Technique**	**Classification rate (%)**
[3]	IGANFIS	98.24
[32]	SANFIS	96.07
[10]	L.V .Q	95,82
[15]	Fuzzy	96,71
[21]	Fuzzy-GA1	97,36

Neuro-Fuzzy Hybrid models improve relatively remarkable performances in diagnosis [28] . There exists many kinds of neuro-fuzzy classifiers such as trainable fuzzy classification systems [20][8], histogram based fuzzy systems [4][14] ,fuzzy sets self organizing classification systems [12][11][16], Neuro-fuzzy classification systems (NeFClass)[27]…

This paper presents the Adaptive Neuro-Fuzzy Inference System (ANFIS), which is well-suited to classification of qualitative input and output variables. The rest of the paper is organized as follows. First, we introduce artificial neural network (ANN) and the neuro-fuzzy approach .Then, the dataset used for breast cancer diagnosis is described in the second section. The final section views and analyzes results obtained for classification of the breast cancer probelm.

2. NEURO-FUZZY SYSTEMS

Neural networks and fuzzy logic are two approaches that are widely used to solve classification and pattern recognition problems. The main advantage of neural networks is their learning capabilities and their ease of implementation. In the other hand , the non interpretability of their results is a major disadvantage (black boxes). The fuzzy inference systems can interpret their results using a knowledge base (rule base). The joint use of neural networks and fuzzy inference systems can exploit the advantages of both methods.

Table 2 below gives a comparative view between the two approaches:

TABLE 2: Comparison between neural networks and fuzzy inference systems [18]

Artificial neural network	**Fuzzy inference system**
Difficult to use prior rule knowledge	prior rule base can be incorporated
Based on Learning	Can not learn
Black box	Interpretable(If – Then rules)
Complicated learning algorithms	Simple interpretation and implementation
Difficult to extract knowledge	Knowledge can be available

We can say that neuro-fuzzy systems are connectionist models that allow learning as artificial neural network , but their structure can be interpreted as a set of fuzzy rules .Fuzzy logic and neural networks form the basis of the majority aided diagnostic intelligent systems.It would be interesting to combine the two approaches to exploit both advantages.

Different models exist for combining fuzzy logic and neural networks. In this paper we diagnose breast cancer using the ANFIS approach (Adaptive Neuro Fuzzy Inference System) proposed by Jang [9].

2.1. ANFIS Architecture

The Anfis (acronym of Adaptative Neuro Fuzzy Inference System) is a neuro-fuzzy model proposed by Jang in [9] . Jang combined both Fuzzy Logic and Neural Network to produce a powerful processing tool named Neuro-Fuzzy Systems that have both Neural Network and Fuzzy Logic advantages and the most common one is ANFIS .Actually, this tool is like a fuzzy inference system, but the difference is in the use of a back propagation algorithm for minimizing the error [29**]**.The Anfis architecture is illustrated in the **figure 2**:

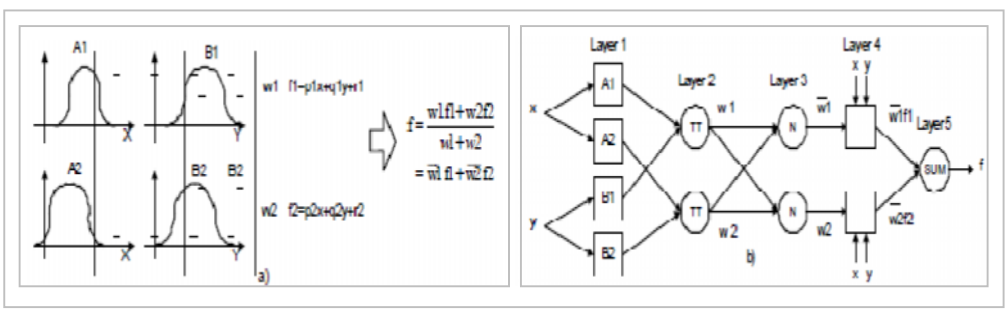


Figure 2. a) A two input first-order b) Equivalent Anfis Architecture Sugeno fuzzy model with two rules

For simplicity ,we assume that the fuzzy inference system under consideration has two inputs x and y and one output z .for a first-order Sugeno fuzzy model, a common rule set with two fuzzy if-then rules is the following:

R1: If x is A1 and y is B1 then f1=p1x+q1y+r1 (1)

R2: If x is A2 and y is B2 then f2=p2x+q2y+r2 (2)

Figure 2.a) gives an illustration about the reasoning mechanism for this Takagi-Sugeno Model. **Figure 2.b)** shows the corresponding equivalent ANFIS architecture where nodes of the same layer have similar functions.

As illustrate **figure 2.b)** ,the Anfis architecture contains fixed nodes (circular) and adaptive nodes (square) that allows representing the basic rules carried out by an adaptative network .

Note that the structure of this adaptative network is not unique, we can combine layer 3 and 4 to obtain an equivalent network with only four layers .The first hidden layer is for fuzzification of the input variables and T-norm operators are deployed in the second hidden layer to compute the rule antecedent part. The third layer normalizes the rule strengths and the consequent parameters of the rules are determined in the fourth layer **[1]**. Output layer computes the overall input as the summation of all incoming signals **[1]**

2.2. Hybrid learning algorithm

Table 3 shows how to apply the hybrid learning algorithms to indentify Anfis parameters. The learning algorithm is composed of two phases:

- In the forward pass of the hybrid learning algorithm, node outputs values go forward until layer 4 and the consequent parameters are identified by the least squares method [9]
- In the backward pass, the premise parameters are adjusted using the gradient descent method [9].

TABLE 3 . Two passes in the hybrid learning procedure for ANFIS [18]

	Forward Pass	**Backward Pass**
Premise Parameters	Fixed	Gradient Descent
Consequent Parameters	Least-squares estimator	Fixed

The output ‘f‘ in **Figure 2 b)** can be written as:

$$f = \frac{w1}{w1+w2} f1 + \frac{w2}{w1+w2} f2 \qquad (3)$$

$$= \overline{w1}\,(p1\,x + q1\,y + r1) + \overline{w2}\,(p2\,x + q2\,y + r2) \qquad (4)$$

$$= (\overline{w1}\,x)p1 + (\overline{w1}\,y)q1 + (\overline{w1})r1 + (\overline{w2}\,x)\,p2 + (\overline{w2}\,y)q2 + (\overline{w2})r2 \qquad (5)$$

This way an adaptive network that is functionally equivalent to a first order Sugeno fuzzy model is constructed. [31]

3 . DADASET DESCRIPTION

This section describes the database used for medical diagnosis problem. In this study we used the dataset provided by researchers at the University of Wisconsin. The dataset was obtained from the University of California Irvine (UCI) Machine Learning Repository [19**]** consist of 699 data with 65.5% classified as benign and 34.5% as malignant The Wisconsin breast cancer diagnosis (WBCD) database is the effort made at the University of Wisconsin Hospital for accurately diagnosing breast masses based solely on an FNA (Fine Needle Aspirates) test [6][21] .Nine visually assessed charac-teristics of an FNA sample considered relevant for diagnosis were identified, and assigned an integer value between 1 and 10**[**26] .The measured variables are described in **Table 4**.

TABLE 4. Attributes of the diagnostic base

Configuration	Number of rules	Learning Error	Classification rate %
2*2*2*2*2*2	64	0.29843	0.9825
2*3*3*3*2*2	216	0.16176	0.8904
2*2*2*3*2*3	144	0.16982	0.9386

The Wisconsin Breast Cancer Diagnosis (**WBCD**) problem involves classifying a presented case as to whether it is benign or malignant [22],[30].There are several studies based on this database. Among them, researchers having interpretability of the diagnostic as a prior objective have applied the method of extracting boolean rules from neural networks [22],[23]**.** Our work for the **WBCD** problem showed that it is possible to obtain diagnostic systems exhibiting high performance, coupled with interpretability and a confidence measure.The database itself consists of 699 cases including 16 unavailable instances as shown in **Table 5**

TABLE 5 . The Wisconsin Breast Cancer Data base

Case	CT	UCS	UCH	MA	SEC	BN	BC	NN	M	Diagnosis
1	5	1	1	1	2	1	3	1	1	Benign
2	5	4	4	5	7	10	3	2	1	Benign
….	…	…	…	…	…	…	…	…	…	…
683	4	8	8	5	4	5	10	4	1	Malignant

4. RESULTS AND DISCUSSION

4.1. Choice of Parameters

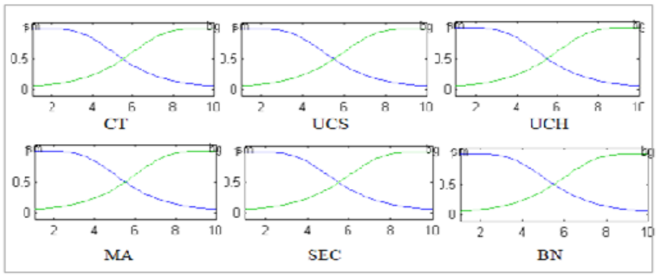
we note that choice of the number of membership functions is important for the development of neuro-fuzzy systems. This affects the number of rules generated. Our goal is to obtain a high performance with a reasonable number of rules. In this study, we have used information gain algorithm [3] in order to reduce the feature number of the Wisconsin breast cancer database (WBCD), So we obtain 6 features instead of 9. **Table 6** shows some results obtained for our experimentation:

TABLE 6. Error and classification rate for different configurations

Attributes	Signification
CT	Clump Thickness
UCS	Uniformity of Cell Size
UCH	Uniformity of Cell Shape
MA	Marginal Adhesion
SEC	Single Epithelial Cell Size
BN	Bare Nuclei
BC	Bland Chromatin
NN	Normal Nucleoli
M	Mitosis

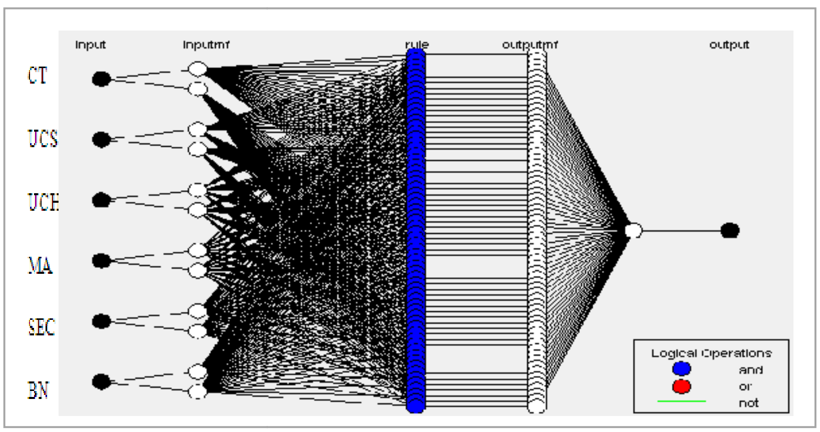
We have assigned the values of error threshold to 0.001. Besides, we adopt the TSK as the structure for the Fuzzy model. After several trials, we have chosen to assign two membership functions for each descriptor in order to reduce the size of rules generated (sm: small, bg: big). Regarding the type of membership functions, we chose generalized bell functions (to guard the readability of results).

Initial parameters of membership functions are shown in the following figure 3:



The structure of the proposed neuro-fuzzy model is presented in the following **figure 4**:

Figure 3. Initial membership functions (before learning)



After choosing these initial configurations, we start learning phase, using the back propagation algorithm and the hybrid method (based on back propagation and least squares techniques).

4.2. Generated Fuzzy rules

At the end of learning, membership parameters will be modified as shown on **figure 5:**

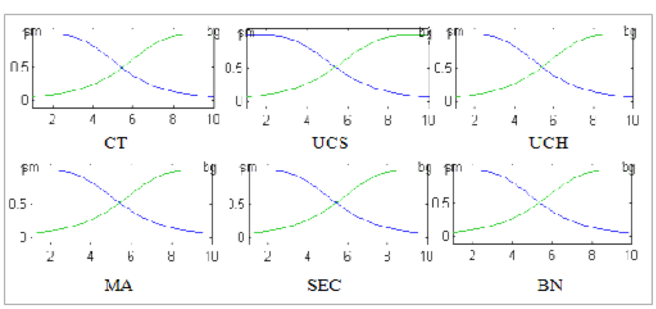


Figure 5. Final membership functions (after learning)

Rules generated by our neuro-fuzzy model are divided into two groups:

- 1st group : Fuzzy rules indicating benign class (1,2,5,7,8,9,11,14,17,20,22,25,31,33, 39,45, 50,51,53,56) .
- 2nd group : Fuzzy rules indicating malignant class (3,4,6,10,13,15, 16,18,19,21,23, 24,26, 27,28,29,30,32,34,35,36,37,38,40,41,42,43, 44,46,47,48,49,52,54,55,57, 58,59,60, 61,62 ,63,64)

We coded the two outputs by two classes:

* Benign Class = 0 and * Malignant class = 1.

4.3. Results Analysis

The performances of the neuro-fuzzy classifier were evaluated using the following parameters:

1. CC=TP+TN/(TP+TP+FP+FN)*100 is the correct classification rate.
2. Error_rate = FP+FN/(TP+TP+FP+FN)*100 is the error rate
3. Se : Sensitivity= TP/(TP+FN)*100 is the true positive rate.
4. Sp : Specificity =TN/(TN+FP)*100 is the fraction of nonevents that has been correctly rejected.
5. Nbr TP: is the number of True Positives.
6. Nbr TN: is the number of True Negatives.
7. Nbr FP: is the number of False Positives.
8. Nbr FN: is the number of False Negatives.

Performances of the neuro-fuzzy systems using hybrid and back-probagation algorithms are summarized in **Table 7**:

TABLE 7: Differentes results of Anfis

CC %	**Error rate %**	**Se %**	**Sp %**	**Nbr Tp**	**Nbr Tn**	**Nbr Fp**	**Nbr Fn**	**Type**
98.25	1.75	97.5	98.65	78	146	2	2	hybrid
64.91	35.09	0	100	76	148	0	80	Back-propagation

We note that the hybrid method (which combine back-propagation and least squares for learning) gives better results than back propagation method, because the conclusion of the rules are adjusted using least square method.The confusion matrix showing the classification results of the ANFIS model is given in **Table 8 :**

TABLE 8: Confusion Matrix

Desired & Output result	Benign records	Malignant records
Benign records	**146**	**2**
Malignant records	**2**	**78**

4.3.1. Correctly recognized cases

4.3.1.1. Cancerous cases correctly recognized

We calculated the degree of solicitation (degree of activation between 50% and 100%) for each rule in relation to the number of examples. The results are shown in the following **Table 9** :

TABLE 9: Degree of solicitation for rules in T.P case

Rule	Solicitation degree (%)
64	8/80 = 10%
62	3/80 = 3%
63	4/80 = 5%
58	2/80 = 2,5%

Rules cited in **Table 9** are presented below:

R58: If (CT is **bg**,UCS is **bg**,UCH is **bg**,MA is **sm**,SEC is **sm** and BN is **bg**) then Class = 1
R62:If (CT is **bg**,UCS is **bg**,UCH is **bg**,MA is **bg**,SEC is **sm** and BN is **bg**) then Class = 1
R63:If (CT is **bg**,UCS is **bg**,UCH is **bg**,MA is **bg**,SEC is **bg** and BN is **sm**) then Class = 1
R64:If (CT is **bg**, UCS is **bg**,UCH is **bg**,MA is **bg**, SEC is **bg** and BN is **bg**) then Class = 1
We note that: **Sm** : Small, **bg** : big .

According to these results, Rule **64** has the most important degree of solicitation. We take two examples with a CT higher than 5, so the activated fuzzy rules and their degrees of solicitation are shown below:

1st exemple :

- (CT=8, UCS=10, UCH=10 ,MA=7, SEC=10, BN=10) activates essentially the rule number **64** with a degree of solicitation equals to 82.25%.

2nd example:

- (CT=6, UCS=10, UCH=10, MA=10 ,SEC=10, BN=10) activates basically rules number **64** and **32** with respectively degree of solicitation equal to 62.11% and 37.71%. Rule **32** is given below:

R32:If (CT is **sm**,UCS is **bg**,UCH is **bg**,MA is **bg**,SEC is **bg** and BN is **bg**) then Class = 1 .
For the two previous examples the CT has gone beyond normal which makes the malignancy.

4.3.1.2. Non cancerous cases correctly recognized

The degrees of solicitation for rules that represent the non-cancerous cases correctly recognized are presented in the **Table 10**:

TABLE 10: Degree of solicitation for rules in T.N case

Rule	Solicitation degree (%)
1	140/148 = 95%
33	3/148 = 2%

Rules presented in table 9 are:

R1: If (CT is **sm**, UCS is **sm**, UCH is **sm**, MA is **sm**, SEC is **sm** and BN is **sm**) then Class = 0.
R33: If (CT is **bg**, UCS is **sm**, UCH is **sm**, MA is **sm**, SEC is **sm** and BN is **sm**) then Class = 0.
We note that the first rule has the greatest solicitation degree.

If we take the first example in the diagnostic database having the following parameters:

- (CT = 1,UCS = 1 ,UCH = 1 , MA =1,SEC =2 ,BN =4) has activated :

- The first rule (rule **1**) with a degree of 81.40%.
- The second rule (rule **2**) with a degree of 2.72% .Noting that **Rule 2** says:
If (CT is **sm**,UCS is **sm**,UCH is **sm**,MA is **sm**,SEC is **sm** and BN is **bg**) then Class = 0

4.3.2 . Misrecognized Cases:

4.3.2.1. Non cancerous cases predicted as cancerous (FP)

Among the non-cancerous cases, our model has recognized two cases as cancerous, but only one example has a degree of solicitation between 50% and 100%. The **Table 11** shows this case.

TABLE 11 : Degree of solicitation for rules in F.P case

Rule:	Solicitation degree % :
33	1/148 = 0.006

4.3.2.2. Cancerous cases predicted as non cancerous (FN)

We have just two examples where cancerous cases have been predicted as non cancerous with degree of solicitation less than 40% in most cases.

5. CONCLUSION

This work presents a knowledge extraction and classification of breast cancer disease using basically a neuro-fuzzy approach for system design, able to explain human decisions. We can say that the proposed method is an important tool which can be integrated in a CAD (computer aided diagnosis) for assisting in diagnostic decision making, with providing an understandable explanation of the underlying reasoning. According to results obtained in table **7,8** and others, we can say that the used method is very promising approach in medical data recognition .

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