An Efficient Spiking Neural Network Approach based on Spike Response Model for Breast Cancer Diagnostic

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Abstract: *This study investigates the efficiency of the one-layered Spiking Neural Network (SNN) on the enhancing of the breast cancer diagnostic results. The proposed network is based on Spike Response Model (SRM) with multiple delays per connection. Beside its simplicity, this model allows to modeling the production of a biologically realistic response to incoming synaptic events. By using a supervised learning, the training process was founded around of an error-back propagation algorithm depending only on the time of the first spike emitted. In experimentation, our approach was exclusively tested on Wisconsin Breast Cancer Database (WBCD). The results were evaluated in accuracy classification and the area under Receiver Operating Characteristics (ROC) Area Under ROC Curve (AUC). In summary, we achieved 99.26% of accuracy classification with an AUC equal to 0.992.*

Keywords: *SNN, SRM, a gradient descent rule, WBCD.*

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1. Introduction

The breast cancer is fatal disease that became leading cause of mortality in female premature death. The pathology stage remains important information in clinical diagnostic where the tumor is of two aspects: Non-cancerous (benign) and cancerous (malignant). The early detection can prevent the disease and increases the chances for successful treatment. Therefore, among the technical of medical decision support systems, the breast cancer diagnostic appears as the most studied in research works. Several approaches were tested to improve the diagnostic results or simply for proving their efficiency, as benchmark case, to solve this classification problem.

Some classifiers were founded around of neuronal approach. The performed results were around 95.74% and 98.8% of accuracy in [14] with using several models of classic Artificial Neural Network (ANN). Other approaches combined ANN with association rules in [12, 27] and genetic algorithms in [19] performed, respectively, the accuracy of 98.24%, 97.4% and 97.2%.

Actually, in the breast cancer diagnostic, the most interesting decision support systems based on ANNs were models with closest biological behaviors. The results reached the accuracy of 99.26% in [16] by using met plasticity rule and 99% in [17] with integration of theta neurons.

However, the highest accuracy classifications were reached by Support Vector Machine (SVM) systems.

In [28] the SVM obtained an accuracy of 99.54%. Also, the reported accuracy in [1] was 99.51%, the method combined SVM with feature selection. More recently, other combined method using adaptive SVMs with fuzzy c-means clustering achieved 99.87% of accuracy [22]. Also, the Learning Classifier Systems (LCS) was experimented in the works of [13].

In this study, we tried to prove that a simple neural architecture based on spiking neuron unit is able to realize a classification problem, unlike classical neuron model. With the concept of error back propagation, the plasticity rule used is more adapted for the temporal data where the input data are supposed to be encoded on multiple spikes emitted [5]. In spite of that, the algorithm is perfectly fixed with the static data used in our case.

The choice of the Spike Response Model (SRM) was founded on the efficiency of the model in classification problems [3, 5, 21, 26] or segmentation [18]. In first section, we describe the SRM that used in our classifier. Several formulations were proposed to describe the behavior of this model. So, we had given a detailed overview of the mathematical formulas used. Also, we overviewed the learning rules characteristics.

Finally, in experimentation, we evaluated the ability of Spiking Neural Network (SNN) to correctly classify the sample of the Wisconsin Breast Cancer Database (WBCD). The sensitivity and specificity determine the effectiveness of any breast cancer screening methodology [20]. Hence, these two rates were represented by the Receiver Operating Characteristics (ROC) which provides the most comprehensive description of diagnostic accuracy available to date.

2. Spike Response Model

Proposed and explicitly detailed by Gerstner [8, 9] the SRM is a generalization of the Leaky Integrate and Fire (LIF) model as reduction of a complex biophysical model to a phenomenological spiking model [11]. Typically in SRM, a simple thresholding process dominates the production of spikes with two opposite kernel functions that control the state neuron [15].

The most specific function is a measure of refractoriness as shown in Figure 1, which integrated to the IF model, describes a combination of effects, such as increasing threshold, hyperpolarizing after potential and post-action-potential reduced responsiveness.

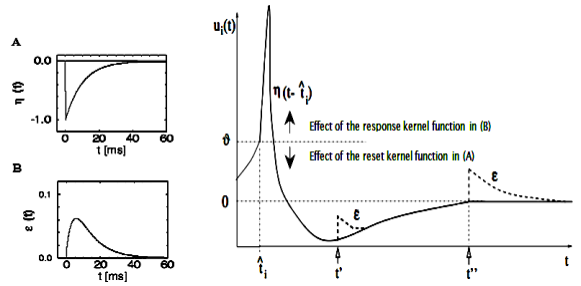

Figure 1. The influence of the reset-kernel function (A) and the spike-response function (B) on Postsynaptic Potential (PSP).

2.1. Description of Model Formulation

In our work, we chose the model with multiple delays per connection as shown in Figure 2. A neuron j is connected with a set of presynaptic neurons Γ_j in limited and fixed set of l delays.

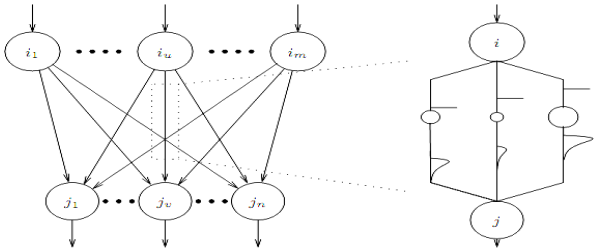

Figure 2. Between unit i and j, single connection composed by multiple weighted and delayed synapses [4].

The reset kernel η and the spike-response function ε formulate Equation 1 that defines how is calculated the neuron potential $u_j(t)$.

$$u_j(t) = \sum_{t_j^{(f)} \in F_j} \eta(t - t_j^{(f)}) - \sum_{i \in \Gamma_j} \sum_{t_i^{(g)} \in F_i} \sum_{k=1}^{l} w_{ji}^{k} \varepsilon(t - t_i^{(g)} - d^k) \quad (1)$$

Where w_{ji}^{k} denotes the weight associated with synaptic terminal k as a PSP of standard height with delay d^k. The firing of neuron depends on increasing of its potential and the threshold value ϑ. A spike is sent each time where, $u_j(t)$ reached ϑ and this moment is denoted as a spike-time $t^{(f)}$.

$$u_j = \vartheta \wedge \frac{du_j(t)}{dt}\Big| t = t^{(f)} > 0 \quad (2)$$

Thus, until the nth emitted spike, all neuron activity is stored on the array of chronologically ordered spike-times.

$$F_j = \left\{ t_j^{(f)} : 1 \le f \le n \right\} : 1 \le f < g \le n \Rightarrow t_j^{(f)} < t_j^{(g)} \quad (3)$$

Clearly, the neuron activity depends on the appropriated choose of formulas that controls its state. In our implementation, the PSP is modeled by the difference between two exponential decays:

$$\varepsilon(s) = \left| exp\left(-\frac{s}{\tau_m}\right) - exp\left(-\frac{s}{\tau_s}\right) \right| H(s) \quad (4)$$

Where denotes the heavy-side step function: $H(s)=0$ for $s \le 0$ and $H(s)=1$ for $s>0$. The rise and decay of the function are determined by the time constants τ_m and τ_m. As well, a simple exponential decay is used in Equation 5 so that refractoriness stage is forced after each spike emitted and the firing can be avoided only shortly afterwards.

$$\eta(s) = -\vartheta exp\left(-\frac{s}{\tau_r}\right) H(s) \quad (5)$$

The same principal of the heavy-side step function was also saved for the $\eta(s)$ formula. The parameter τ_r is another time-constant.

2.2. A Gradient Descent Rule for One-Layered SNN Based in SRM

The definition of the learning-rules requires the knowledge of the network topology and the learning method. In our work, we selected a SNN with one-layered network with supervised learning process. Many studies have proposed supervised learning-rules designed for SNNs [3, 5, 10, 25]. In our work, we use a gradient descent rule proposed in [5] which has a close resemblance to SpikeProg rule [3]. The SpikeProg rule was meant for network architecture with hidden layers, but the factual particularity of this version, used in our work, is in error counting based only on the time of first spike.

In each learning rule, the main objective is to determine the synaptic weights of the spiking neuron network. Therefore, in order to minimize the error measure, all the delayed synapses are modified.

Formally, it's necessary to define for all neurons error value for each spike it fired, in this case, only the first spike time count. The network error is the sum squared error of first spike time of the output neurons j, so later spikes of these neurons are ignored:

$$E_{net} = \frac{1}{2} \sum_{j \in J} \left(t_j^1 - \hat{t}_j^1 \right)^2 \quad (6)$$

Where, $\hat{t}_j^1$ denotes the desired first spike time and t_j^1 represented the calculated first spike time. The parameters that are tuned to reduce this error are the

weight of synapses w_{ji}^{k}. We calculate the derivative of the network error with respect to the weight in order to calculate the appropriate weight change:

$$\Delta w_{ji}^{k} = -\eta \frac{\partial E_{net}}{\partial w_{ji}^{k}} \quad (7)$$

Where η denotes the learning rate. The neuron i can fire multiple times and all these firing times depend on the weight. Finally, after derivations, the formula which expresses the change of the weight concretely as follows:

$$\Delta w_{ji}^{k} = -\eta \frac{-\sum_{t_i^{(g)} \in F_i} \varepsilon'\left(t_j^{(1)} - t_i^{(g)} - d^{k}\right)}{\sum_{i,k} \sum_{t_i^{(g)} \in F_i} w_{ji}^{k} \varepsilon'\left(t_j^{(1)} - t_i^{(g)} - d^{k}\right)} \left(t_j^{(1)} - \hat{t}_j^{(1)}\right) \quad (8)$$

With Equation 8, it is now possible to compute the necessary weight changes that minimize error measure based in first spikes time of the output neurons.

3. Experimentation

In this study, the SNN was applied on the WBCD [29]. The WBCD database was originally collected, as a group of 367 instances, by Dr. William H. Wolberg at the University of Wisconsin-Madison Hospital. Between 1989 and 1992, seven groups were added to the database for a total count of 699 records: 458 benign samples and 241 malignant samples. As shown in Table 1, each record in the database has eleven attributes with an unnecessary attribute in the header marking the sample code. The features of the sample are represented by nine attributes which have an integer value between 1 and 10. The diagnostic is labeled in the last attribute.

Table 1. Wisconsin breast cancer data description of attributes.

	Attribute	Domain
1	Sample Code Number	id number
2	Clump Thickness	1-10
3	Uniformity of Cell Size	1-10
4	Uniformity of Cell Shape	1-10
5	Marginal Adhesion	1-10
6	Single Epithelial Cell Size	1-10
7	Bare Nuclei	1-10
8	Bland Chromatin	1-10
9	Normal Nucleoli	1-10
10	Mitoses	1-10
11	Class	(2 for benign, 4 for malignant)

Among the 699 samples, the dataset contains 16 instances with a single missing attribute values. Consequently, we followed many research works by isolating these data samples for operating only on 683 samples. The class has a distribution of 444 benign samples and 239 malignant samples.

Therefore, we divided the used samples in two sub-sets where 60% of the data is for the training process and the remaining 40% of data for the testing phase. Table 2 illustrates clearly this distribution.

Table 2. Repartition of dataset used.

Class	Training (60%)	Test (40%)	Total
Malignant	144	95	239
Benign	266	178	444
Total	410	273	683

Also, we decided that the isolated 16 instances could be used as a test of noisy data. The bare nuclei measure is missed into all this samples knowing that 2 of these samples are malignant cases and 14 samples are benign.

3.1. Spiking Neural Network: Topology and Parameters

For the diagnostic of breast cancer, we proposed a one-layered SNN based in SRM neurons. Basically, with a feed forward construction, the input-layer serves to receive the incoming stimuli and transfer it as spike trains. Therefore, each feature of WBCD database samples represents an input neuron; in our case nine features. The output-layer includes only one neuron which identifies the case: Benign or malignant. As shown in Figure 3. The duration of the input-signal and the output response is fixed at 20ms.

Fundamentally, the input and output of a spiking neuron is described by a series of firing-times. The input feature is encoded in the spike-time based on a specific thresholding of the values of cytological characteristics.

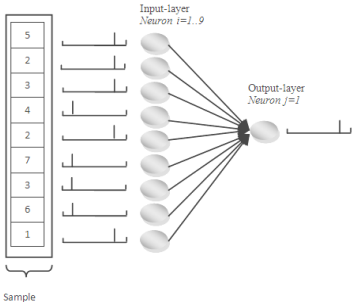

Figure 3. SNN topology.

During the training, we desire that the output-neuron that represents the diagnostic of the input-pattern fires an early spike, at t_d=2ms, when it's malignant case. By opposition, it fires a spike lately at t_d= 20ms when it's benign. Over the generalization procedure, the output neuron specifies this discrimination by testing the phase of firing-time: If the firing is included at the interval [0, 10] ms the sample is qualified as malignant case, besides, the interval [10, 20] ms represents the benign case.

Furthermore, we had explained previously that each of the 9 input-neurons is connected to the output-neuron with l synapses with delays {1, 2, …, 10}ms. In our experimentation, the parameter l has shown a great effect on the enhancing of classification accuracy. The tested values were between 1 and 10 delays.

For the spike-response function $\mathcal{E}$, the values of parameters τ_m and τ_s was varied between 2 and 10 with always τ_m superior to τ_s. We noted that the different values tested had also affected the results more the parameter τ_r of the refractoriness function η initialized at 10. The weights of the connections were initialized to random values from the range [0, 0.5].

3.2. Results: Evaluations and Discussions

In this section, we illustrated and exposed the results of our proposed SNN. To evaluate our approach, we based our evaluation on several rates and plots. First, we used classification accuracy which is a rate that describes the number of samples correctly classified.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (9)$$

Where *TP*: True Positive, *TN*: True Negative, *FP*: False Positive, and *FN*: False Negative.

For the medical diagnostic, generally, we count two specifics measures: Sensitivity and specificity. These rates of a diagnostic test depends on more than just the quality of the test, they also, depend on the definition of what constitutes an abnormal test. The Sensitivity is probability that a test result will be positive when the disease is present (true positive rate) and the Specificity is probability that a test result will be negative when the disease is not present (true negative rate). Equations 10 and 11 illustrated how to calculate these evaluation parameters.

$$Sensitivity = \frac{TP}{TP + FN} \quad (10)$$

$$Specificity = \frac{TN}{FP + TN} \quad (11)$$

For more evaluation, we use the ROC. The graphs and the parameters obtained by ROC are a useful technique for organizing classifier and visualizing this performance [7]. Specifically, the Area Under ROC Curve (AUC) is the most interesting parameters to calculate for measuring of test accuracy. This measure is supposed to be between 0 and 1 and indicate the reliable diagnostic test: More the AUC is close to 1 better it is.

The training process was operated with several configurations based on: l the number of synapses between two units and parameters τ_m and τ_s. The experimentation had demonstrated that these parameters were the most influent parameters where the variation of l value affects classification accuracy and the parameters τ_m and τ_s control the sensitivity and specificity. The learning rate is initially set to 10^{-3} by using the on-line learning method.

For the l number of synapses, the parameter is assigned between 1 and 10 delays in each initialized configuration. The classification accuracy was enhanced only if the value was 5 delays or more where the networks reached easily 98.90% of classification accuracy. The optimal measures were 5 or 7 delays where we achieved 99.26% accuracy. Figure 4 illustrated clearly the classification accuracy with the variation of the number of synapses.

Furthermore, we varied the parameters τ_m and τ_s of spike-response function $\mathcal{E}$ respectively between (3 and 10) and (2 and 8). The τ_m value should always be superior to the τ_s value for obtaining the spiking response. Therefore, we noted that the difference between these two values was superior to 2 then the approach described more sensitivity and less specificity, otherwise, the specificity achieved easily 100% and the sensitivity didn't exceed 97,89% as shown in Figure 5.

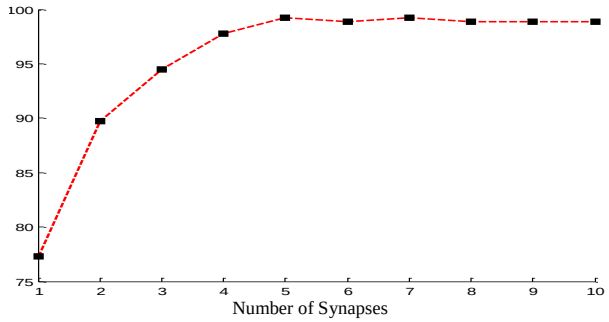

Figure 4. Evolution of classification accuracy with the variation of the number of synapses where, l= 1, …, 10 (τ_m=5 and τ_s=3).

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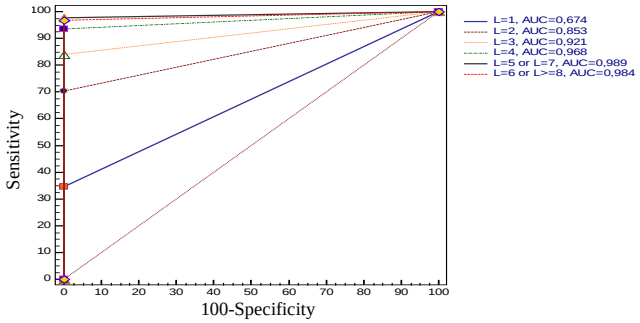

Figure 5. ROC curves of the classifier with variation of number of synapses between units where l= 1, …, 10 (τ_m=5 and τ_s=3).

Figure 6 showed the ROC curves of two tests that achieved 99.26 % of accuracy:

- Test_A: Where τ_m=10 and τ_s=5, the AUC_A= 0,992.
- Test_B: Where τ_m=5 and τ_s=3 the AUC_B= 0,989.

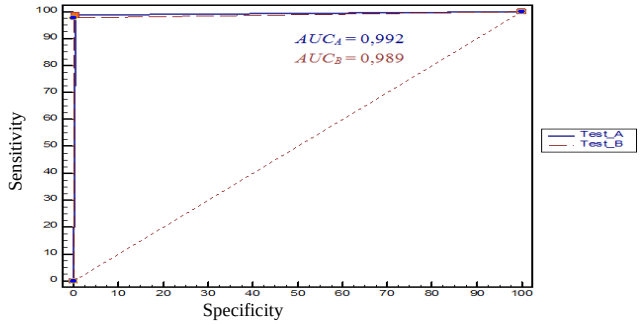

Figure 6. ROC curves of our approach with two optimal values of the parameters τ_m and τ_s.

Finally, the optimal configurations with the best results are marked in Table 3 where for the same classification accuracy; the Test (A) showed the best performance with AUC equal to 0.992 by opposition of the Test (B) that achieved 0.989.

Table 3. The optimal classification accuracies.

Configuration	Test A	Test B
τ_m	10	5
τ_s	5	3
l	7	7
Malignant Samples	94	93
Benign Samples	177	178
Sensitivity	98,94%	97,89%
Specificity	99,43%	100%
AUC	0,992	0,989
Classification Accuracy	99.26%	99.26%

Moreover, the 16 samples with the missing values were tested and achieved 87.5% accuracy. The specificity was equal to 85.71% and for the score of sensitivity was optimal, 100%. The network marked the same classification accuracy results (99.26%) if all the dataset samples have the same missing feature. Besides, the SNN had revealed more robustness, by achieving the same accuracy classification, if each feature was missing one by one in each test launch.

Table 4 illustrated the results obtained by some works. Principally, the most of these applications used neural approach or neural approach combing with other methods: Bayesian net, ants colony and SVMs. The SVMs and artificial met plasticity neural network achieved the leading classification accuracy with 99.54% and 99.26%, respectively. Consequently, we confirm the efficiency of our approach that achieved the same results.

Table 4. Several classification accuracies obtained by neural approach and others methods and applied on WBCD database.

Approach		Authors and Years [ref]	Model	Classification Accuracy (%)
Neuronal	2nd Generation	Setiono [27]	NeuroRule: Rule 2a, Rule 2b	98.10
			NeuroRule: Rule 3	98.24
		kiyan and Yildirim [14]	RBF	96.18
			PNN	97.0
			GRNN	98.8
			MLP	95.74
		Karabatak and Cevdet [12]	Neural network: MLP(9, 11, 1)	95.2
			Neural network and association rules: MLP (8, 11, 1)	97.4
			Neural network and association rules: MLP (4, 11, 1)	95.6
		Mohamed *et al.* [19]	Fuzzy ARTMAP with genetic algorithms	97.2
	3rd Generation	Bohte *et al.* [3]	Multi-layered SNN (64, 15, 2) with SpikeProg rule	97.0
		McKennoch *et al.* [17]	Theta neuron (9, 8, 1) BP rule	99
		Bakó [2]	Implemented hardware SNN	89.5
		Marcano *et al.* [16]	AMMLP (9, 8,1)	99.26
			BPNN (9, 8, 1)	94.51
		Our Study	One-layered SNN (9, 1) based on SRM	99.26
Others		Parpinelli *et al.* [23]	Ant-Miner	96.04
		Übeyli [28]	SVM	99.54
		Akay [1]	SVM-CFS	99.51
		Peng *et al.* [24]	CFW	99.50
		Fallahi and Jafari [6]	Bayesian Net	97.42
			Bayesian Net: Data balancing and remove missing data	97.83
			Bayesian Net : ReliefF,remove missing data, data balancing and sorting data upon feature F	98.15

4. Conclusions

The aim of this paper was to demonstrate the performance of SNN in diagnostic of breast cancer. Our experimentation allows confirming that a simple topology based in SRM was able to realize discrimination between the two classes of the WBCD database. This ability, practically missing in the second generation neurons, indicates an important feature of the spiking neurons models and reduces the duration of learning and generation. Furthermore, the variation of SNN parameters controlled the improving of accuracy classification, sensitivity and specificity. The obtained results proved that our approach return an excellent results with an AUC equal to 0.992.

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