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Artificial Metaplasticity MLP Results on MIT-BIH Cardiac Arrhythmias Data Base

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Abstract

This paper tests a novel improvement in neural network training by implementing Metaplasticity Multilayer Perceptron for cardiac arrhythmias classification. The proposed training algorithm is inspired by the biological metaplasticity property of neurons.The plasticity property of synaptic connections in the brain is modeled in many Artificial Neural Networks as a change in the connection weights of the artificial neurons.Artificial Metaplasticity bases its efficiency in giving more relevance to the less frequent patterns and subtracting relevance to the more frequent ones.We have applied artificial metaplasticity multilayer perceptron (AMMLP) to cardiac arrhythmias classification. The MIT-BIH Arrhythmia Database was used to train and test AMMLPs.The performance of this algorithm is tested using classification accuracy, sensitivity and specificity analysis, and ROC results.The best result obtained so far with the AMMLP algorithm is 98.25% of accuracy. A very promising result compared to the Backpropagation Algorithm (BPA) and recent classification techniques applied to the same database.

Keywords: Artificial Neural Network,Back-Propagation Algorithm (BPA),Cardiac arrhythmias, Classification , Metaplasticity.

I. INTRODUCTION

Artificial Neural Networks (ANN) are widely used in pattern classification within medical fields.They are biologically inspired distributed parallel processing networks based on the neuron organization and decision-making process of the human brain [1].

In this paper a Multi Layer Perceptron (MLP), the most commonly used feedforward neural networks due to their fast operation, ease of implementation, and smaller training set requirements and reliability in classification problems in pattern recognition applications [2][3] is used with the aim of classifying cardiological patterns.

Back Propagation Algorithm (BPA) is one of the most popular training algorithms for MLP. Unfortunately BPA showed some limitations and problems during MLP training. A serious drawback of BPA [4] for conventional MLP training is its slow rate of convergence and, in the search for the global minimum, the risk it runs of being trapped in a local minimum. Several modifications [5],[6],[7],[8]of the original BPA have already been suggested to improve either the convergence or the performance over the original algorithm. However, none of the modifications is capable of delivering satisfactory performance for all problems, in general. Thus, the search for an approach to speed up its convergence and/or for the improvement of general performance of the trained network still remains important. For this reason we present a novel proposal for improved BPA based on Metaplasticity. In Section 5 we will describe the above algorithm.

As is well-known within the ANN field, in1949 Hebb postulated that during the learning phase, synaptic connections between biological neurons are strengthened due to the correlated activity of presynaptic and postsynaptic neurons [9]. This plasticity property of synaptic connections is modeled in many ANNs as a change in the connection weights of the artificial neurons or nodes. Therefore, synaptic plasticity of biological neural networks has been simulated in artificial networks by changing the weight values of the simulated neuronal connections .These weights are the most relevant parameters in ANN learning and performance .Modeling these new discovered properties of biological neurons that follow metaplasticity rules provides a large potential for improving ANN learning.

Metaplasticity is a term originally coined in neuroscience to refer to the emergent higher-order properties of synaptic plasticity itself and their modification.

The main objective of the proposed work is to model and test the biological property of metaplasticity on a multilayer perceptron (MLP) trained with BPA. This interpretation has been modeled in the neural network (NN) training phase.

The well-known MIT-BIH Database [10] was used to test the proposed artificial meta- plasticity with the MLP algorithm (AMMLP). The AMMLP algorithm was then compared with classical backpropagation and other algorithms, recently proposed by other researchers, which were successfully applied to the same database.

For a correct understanding of metaplasticity mechanisms, we will start with an introduction to the synaptic plasticity. In Section 2 we present an introduction to the regulatory mechanisms of neuronal plasticity, to allow the understanding of the biological metaplasticity mechanisms. Then we introduce the hypothesis on the relationship between metaplasticity and Shannon's information theory, which will lay the foundation for understanding the proposed model. Section 3 describes the implementation of the AMP algorithm in the MLP neural network, trained with the BPA. Section 4 presents a detailed description of the database and the algorithms. The experimental results are presented in section 5.a comparison and discussion of these results is shown in section 6. Finally section7 summarizes the main conclusions.

II. METAPLASTICITY MECHANISMS

Neuroplasticity is also called Brain plasticity .it is a common term used by neuroscientists, referring to the brain's ability to change at any age. This flexibility plays an incredibly important role in our brain development and in shaping our distinct personalities. Activity dependent modifications of synaptic efficacy are fundamental to the storage of information in the brain.

Learning and memory in the brain likely occur through activity dependent; long lasting changes in synaptic transmission. Two opposite activity – dependent synaptic modifications have been identified so far; long term potentiation and long term depression.

Synapses are neural structures that modulate presynaptic activity, converting this activity into a higher or lower postsynaptic activation (voltage). The magnitude that relates postsynaptic voltage with presynaptic activity is called synaptic efficiency or synaptic weight.

The direction and the degree of the synaptic alteration are functions of postsynaptic depolarization during synaptic activation. Upregulation, reinforcement of synaptic efficacy, is termed long-term potentiation (LTP), whereas down regulation, is known as long-term depression (LTD).LTP and LTD are believed to be fundamental to storage of memory in the brain and hence learning. The induction of synaptic changes in the levels of neural activity is explained in Fig.1.

Synaptic plasticity also depends on prior synaptic activity. Activity-dependent modulation of subsequent induction of synaptic plasticity, termed Metaplasticity.

The concept of biological metaplasticity was defined in 1996 by Abraham [11] and now widely applied in the fields of biology, neuroscience, physiology, neurology and others [11,12].

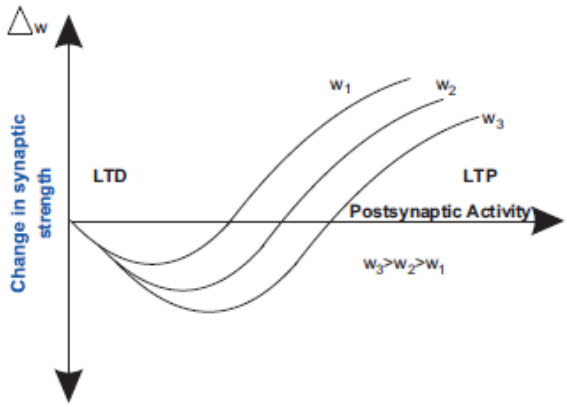

Fig. 1. Changes in synaptic strength due to postsynaptic activity in biological neurons.

If postsynaptic activity is high, the curve will move to the right, reinforcing the LTP. This graphic shows a family of curves in which each curve indicates the variation in weight, Δw, respective of the neuron's activation. The parameter that defines which curve must be used is the value of the synaptic weight, w. For higher values of the weight, the curve elongates further to the right.

The Metaplasticity is defined by many scientists as the plasticity property of synaptic plasticity [13] [14]. The prefix "meta" comes from Greek and means "beyond" or "above", is used to indicate a higher level of plasticity, expressed as a change or transformation in the way synaptic efficacy is modified.

Metaplasticity can be represented as variations in curve elongation with respect to the level of activity and implies a shift of the LTP threshold according to the weight strength of the synapse [13]. Fig. 1 graphically illustrate this idea.
An understanding of metaplasticity might yield new insights into how the modification of synapses is regulated and how information is stored by synapses in the brain. For a correct understanding of this mechanism we will start with an introduction to synaptic plasticity.

A. Synaptic plasticity

Synaptic plasticity refers to the modulation of the efficacy of information transmission between neurons and is related to the regulation of the number of ionic channels in the synapse. The mechanisms responsible for synaptic plasticity involve both molecular and structural modifications that affect synaptic function, either enhancing or depressing neuronal transmission. These modifications include the redistribution of postsynaptic receptors [15]. The first model of synaptic plasticity was postulated by Hebb and is commonly known as the Hebb rule [9].

B. Metaplasticity vs intrinsic plasticity

Metaplasticity generally prevents null or saturated synaptic weights. However, these extreme situations cannot be completely prevented. Intrinsic plasticity regulates the position(rightward shift) of the neuron's activation function according to previous levels of activity[16], [17]. Metaplasticity uses intrinsic plasticity to exclude nullification or saturation of synaptic weight. Metaplasticity contributes to neuronal homeostasis, maintaining individual neuron activity levels and, ensuring that neither nullification nor saturation occurs [18].

C. Metaplasticity and Shannon's information theory

The most efficient model of Artificial MetaPlasticity (as a function of learning time and performance)is the approach that connects metaplasticity and Shannon's information theory, which establishes that less frequent patterns carry more information than frequent patterns [19]. This model defines artificial metaplasticity as a learning procedure that produces greater modifications in the synaptic weights with less frequent patterns than frequent patterns, as a way of extracting more information from the former than from the latter.As biological metaplasticity, AMP then favors synaptic strengthening for low-level synaptic activity, while the opposite occurs for high level activity.In this paper it has been implemented and tested for a MLP over MIT-BIH.

III. BACKPROPAGATION ALGORITHM AND AMP

The AMP implementation applied tries to improve results in learning convergence and performance by capturing information associated with significant rare events. It is based on the idea of modifying the ANN learning procedure such that un-frequent patterns which can contribute heavily to the performance are considered with greater relevance during learning without changing the convergence of the error minimization algorithm. It is has been proposed on the hypothesis that biological metaplasticity property may be significantly due to an adaptation of nature to extract more information from un-frequent patterns (low synaptic activity) that, according to Shannon's Theorem, implicitly carry more information.

In this paper an MLP, the most commonly used feed forward neural networks due to their fast operation, ease of implementation, and smaller training set requirements and reliability in classification problems in pattern recognition applications is used with the aim of classifying cardiological patterns.
Ropero-Pelez [12], Andina [20] and Marcano-Cedeno [21] have introduced and modeled the biological property metaplasticity in the field of ANNs, obtaining excellent results.
The idea proposed in this paper defines AMP as a learning procedure to improve the basic error minimization algorithm used to train a Multi Layer Perceptron manipulating the error objective function in order to give more relevance to less frequent training patterns and to subtract relevance to the frequent ones. This model of AMP is represented in Fig 2.

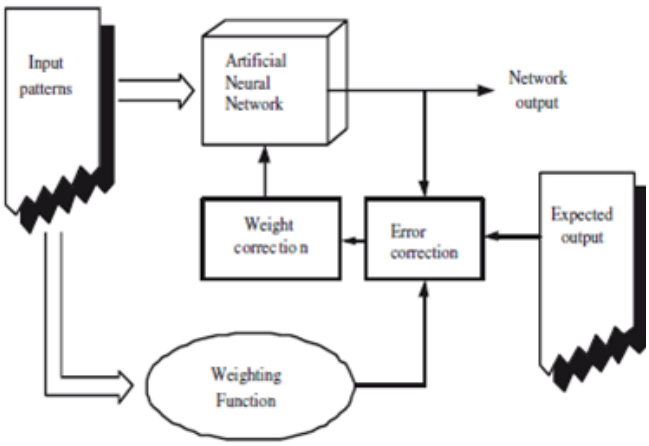

Fig 2: The block diagram presents the weighted training

IV. MATERIALS AND METHODS

Cardiovascular diseases (CVDs) are a group of disorders of the heart and blood vessels [22].They are the number one cause of death globally: more people die annually from CVDs than from any other cause, this is what was stated by the World Health Organization [23]. An estimated 17.3

million people died from CVDs in 2008, representing 30% of all global deaths. During 2011 and 2012, 44.5% of deaths in Algeria are due to heart. To reduce the number of disabilities and deaths caused by heart attack, it is necessary to have an effective method for early detection and early treatment [24] .
The proposed artificial metaplasticity algorithm (AMMLP) is here applied to the detection of cardiac arrhythmias. Because of its relevance, this problem is the subject of many researches. The MIT-BIH Arrhythmias Database has been used to test the AMMLP.

A. overview of the MIT-BIH database

The MIT-BIH Arrhythmia Database was the first generally available set of standard test material for evaluation of arrhythmia detectors, and it has been used for that purpose as well as for basic research into cardiac dynamics at about 500 sites worldwide since 1980 [25].
The Database contains 48 half-hour excerpts of two-channel, 24-hour, ECG recordings obtained from 47 subjects included 25 men and 22 women.

B. Data preparation

From 109871 annotated heartbeats (ECG beats examined by specialists in MIT-BIH.[10].[25])), 1000 were selected for this study, which contain 4 different waveforms related to cardiac arrhythmias target.
Sixteen different patients have been considered in the experiments (taken from MIT-BIH), We have limited the number of patients, taking part in the experiments, to provide at least different arrhythmia cases (N,PVC,RBBB and LBBB). Normal beat (N) ;Premature ventricular contraction (PVC) ; Right bundle branch block (RBBB) and Left bundle branch block (LBBB) are extracted according to the MIT-DB annotation files.

C. Features selection

Features are chosen with the help of specialists in cardiology, we took the descriptors that seem to be most important following the characteristics of the cardiac arrhythmias needed to classification. The eleven features are defined in table 1.

D. Application of Artificial Metaplasticity Algorithm to cardiac arrhythmias classification

The Backpropagation (BP) algorithm presents some limitations and problems during the MLP training [21]. The artificial metaplasticity on multilayer perceptron algorithm (AMMLP) tries to improve BP algorithm by including a variable learning rate η(x) in the training phase affecting the weights in each iteration step based on an estimation of the real distribution of training patterns. That is if s, j, i ∈ N are the MLP layer, node and input counter respectively, for each W(t) component $\omega_{ij}^{(s)}(t) \epsilon R$, where W(t)is the weight matrix, we can express the weight reinforcement in each iteration as:

Attributes	Meaning
Duration P	The width of the P wave
PR interval	The distance between the beginning of the P wave and the beginning of QRS
QRS complex	The distance between the beginning of the Qwave and the end of the S wave
Duration T	The width of the T wave
ST segment	The distance between the end of the S wave or R and the beginning of the T wave
QT interval	The distance between the beginning of QRS and the end of the T wave
RR previous: RRp	the distance between the peak R of the present beat and the peak R of the previous beat.
RR next : RRn	RRn:the distance between the peak R of the present beat and the peak R of the following beat.
RDI (delay of the deflexion)	From the beginning of QRS to the top of the latest wave of positivity R peak.
beat duration	The distance between the beginning of the P wave and the end of the wave T.
RRp / RRn	The ratio RRp / RRn

Table 1: The various descriptors

$$\omega_{ij}^{(s)}(t+1) = \omega_{ij}^{(s)}(t) - \eta(x)\frac{\partial E[W(t)]}{\partial \omega_{ij}} \quad (1)$$

$$= \omega_{ij}^{(s)}(t) - \eta\frac{1}{f_X^*}\frac{\partial E[W(t)]}{\partial \omega_{ij}} \quad (2)$$

Being η ϵ R+ a parameter for the learning rate, E[W(t)] the error function to be minimized and fx the weighting function assuming that the distribution function of patterns is Gaussian [20],[21].

$$f_X^*(x) = \frac{A}{\sqrt{(2\pi)^N}.e^{B\sum_{i=1}^{N} x_i^2}} \quad (3)$$

Where N is the number of neurons in the MLP input layer, and parameters A and B ϵ R+ are algorithm optimization values empirically determined which depend on the specific application of the AMLP algorithm.
fx has high values for infrequent x values and close to 1 for the frequent ones and can therefore be straight forwardly applied in weights updating procedure to model the biological metaplasticity during learning [21].

V. RESULTS

In this section we present results of experiments to test the behavior of the AMMLP proposed method, as well as compare it with classical Backpropagation MLP.
All the models used in this study were trained and tested with the same data and validated using 10-fold cross-validation. The MLP and AMMLP proposed as classifiers for cardiac arrhythmias were implemented in MATLAB (software MATLAB version 7.4, R2007a) and computer Pentium IV of 3.4 GHz with 2 GB of RAM. The eleven attributes detailed in Table 2 were used as the inputs of the ANNs.
Table 3, shows the network structure, metaplasticity parameters, epochs, mean square error (MSE) and numbers of patterns used in the training and the testing of the MLP and AMMLP classifiers.

A. *The AMMLP algorithm*

1.Network structure used in the experiments:

(a) Number of input neurons equal to the number of attributes of the records in the database (plus the bias input).
(b) Number of hidden layers: 1.
(c) hidden neurons: 8 (a compromise solution found empirically to achieve the results with a simple structure)
(d) Output neurons: 5 (4 classes for Normal PVC, RBBB, LBBB and class 5 for others)
(e) Learning rate η =1
(f) Activation function is sigmoidal with value between [0,1].

2. Initialize all weights in weight matrix W randomly between [- 1,1]
3. Training phase

(a) AMP is modeled by applying the weight function represented in Eq. (3) to the BP weights updating during the training phase
(b) Test training conditions
i. if epochs = 500
stop training
ii. if Mean Squared Error,
MSE = 0.001
stop training

B. *Network structure selection*

To select the best configuration for each model used in this study, we tested different network structures and parameters. Table 2 shows the best architectures for each model.

C. *Measures of quality*

To evaluate the performance of the proposed classifier, three measures are used and defined as follows:
Where TP, TN, FP, and FN stand for true positive, true negative, false positive and false negative, respectively. If for example a segment with the V arrhythmia is classified as the V, then it is said that the segment is classified TP. On the other hand if a non-V segment is classified as non-V, then it is said that the segment is classified TN. Any non-V segment which is classified a V segment by mistake will produce a FP, while any V segment which is classified a non-V segment by mistake will produce a FN result.

Types classifiers	Network structure			Metaplasticity parameters		Mean squared error	Epochs	Number of patterns
	I	HL	O	A	B			
AMMLP	11	8	5	39	0.5	0.001	500	1000
MLP	11	8	5	NA	NA	0.001	500	1000

Table 2:Network parameters applying to the MIT-BIH database.
*NA: Not Apply.

D. Model evaluation

For test results to be more valuable, a k-fold cross-validation is used among the researchers because it minimizes the bias associated with the random sampling of the training [26]. In this method, the whole data are randomly divided into k mutually exclusive and approximately equal size subsets. The classification algorithm is trained and tested k times. In each case, one of the folds is taken as test data and the remaining folds are added to form training data. Thus k different test results exist for each training-test configuration [27]. The average of these results provides the test accuracy of the algorithm [26]. A 10-fold cross-validation is used in all of our experiments by separating the selected 1000 samples randomly into 10 subsets with 100 records each and then taking each subset as test data in turns.

E. Performance evaluation

In this study, the models were evaluated based on the accuracy measures discussed above (classification accuracy, sensitivity and specificity). The results were achieved using 10-fold cross-validation for each model, and are based on the average results obtained from the test data set for each fold. The results obtained are showed in Table 3.

As seen in Table 3, the results obtained by AMMLP algorithm are superior to the ones obtained by MLP. The reported results (Table 4), validated by means of the 10-fold cross-validation method, show that the Artificial metaplasticity model produces a higher accuracy than the MLP model. Average of the AMMLP model was 98.25% accurate with sensitivity and specificity rates of 98.3% and 97.79%, respectively. MLP model obtained a prediction average accuracy of 93.72% with a sensitivity rate of 92.34% and a specificity rate of 95.38%.

Fold N	Multi layer Perceptron			Artificial Metaplasticity MLP		
	Accuracy%	Sensitivity%	Specificity%	Accuracy%	Sensitivity%	Specificity%
1	92.84	87.37	98.34	98.91	98.87	98.94
2	97.06	98.31	94.73	99.63	99.43	100
3	94.51	87.42	98.31	99.26	100	97.89
4	91.18	91.12	91.67	97.59	98.52	96.56
5	90.27	90.11	91.27	92.81	91.6	92.73
6	95.89	95.65	96.78	99.06	100	97.59
7	89.13	81.48	100	97.83	96.29	100
8	97.12	100	92.47	100	100	100
9	96.89	93.8	100	99.97	100	99.02
10	92.34	98.23	90.29	97.47	98.29	95.2
Average	93.72	92.34	95.38	**98.25**	**98.3**	**97.79**

Table3: Results for 10-fold cross-validation for all folds and AMMLP and MLP models. Bold values highlight the best results obtained in this research.

F. Performance results ROC

Receiver operating characteristic (ROC) curve: The receiver operating characteristic (ROC) curve is a two-dimensional measure of classification performance that is widely used in biomedical research to assess the performance of diagnostic tests [28]. A ROC curve is a plot of sensitivity vs specificity, or equivalently, the true positive fraction vs the false positive fraction, computed from the application of a series of thresholds to the system output.ROC graphs plot false positive specificity rates on the x-axis and true positive sensitivity rates on the y-axis. A simple, easy to implement approach for generating ROC curves involves collecting the probabilities for all the various tests, along with the true class labels of the corresponding instances, and generating a single ranked list based on the data [28]. If the ROC curve rises rapidly towards the upper right-hand corner of the graph, or if the area value of the curve is large, the test can be described as working well. An area close to one indicates that the test is reliable, while an area close to one half indicates that the test is unreliable. In this case, the ROC curve to demonstrate the superiority of AMMPL over BPA has been used. The resulting ROC curve of our proposed model is presented in Figures 3 and 4.

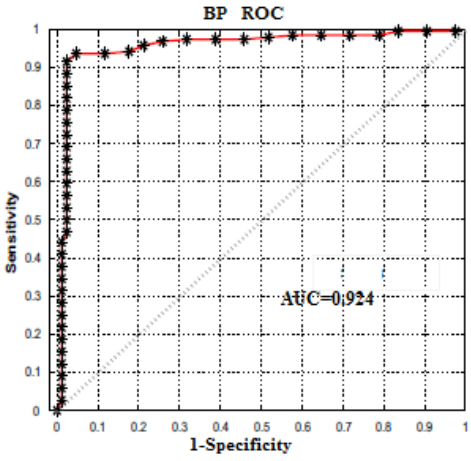

Fig 3: ROC curve of the classifier BPA with an AUC of 0.924

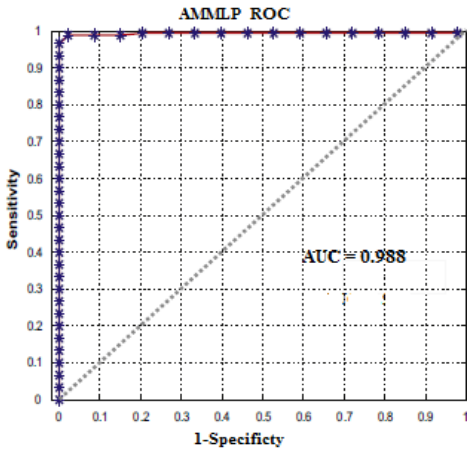

Fig 4: ROC curve of the classifier AMMLP with an AUC of 0.988.

VI. COMPARISON AND DISCUSSION

For comparison purposes, Table 4 gives the classification accuracies of our method and previous methods applied to the same database. As can be seen from the results, our AMMLP method obtains excellent classification accuracy.

We report that the empirical results of AMMLP show a great potential, in terms of improving learning and therefore performance in most cases, no matter what multidisciplinary application it is applied to [27],[29]. The results obtained by the proposed AMMLP algorithm in this paper are among the best compared with the other state-of-the-art methods. The AMMLP is only beat by Gothwal H. et al., [37] and Yu S.N et al., [35] who obtained accuracies of 98.48% and 98.36% respectively (see Table 4). It must be taken into account that in these two better methods a preprocessing phase is applied, Fast Fourier Transform in one case and Independent Component Analysis in the other.

Note that in the work of [37], they use just 5 neurons in the input layer. And in the application of [35], the authors use only 23 independent components in the input layer in order to recognize cardiac arrhythmias with an accuracy of 98.36%.

Authors (year)	Method	Accuracy%
Hu, Y.et al [29] (1997)	Expert Approach	94.00
Minami, K et al [30] (1999)	Fourier-NN	98.00
Osowski, S et al [31] (2001)	Fuzzy Hybrid NN	96.06
Owis M.I et al [32] (2002)	Blind Source Separation.	96.79
Prasad, G et al [33] (2003)	ANN	85.04
Dayong G et al [34](2004)	NN Bayesian	90.00
Yu S.N et al [35](2008)	ICA-NN	98.36
Y.Benchaib et al [36](2009)	MLP BPA	95.12
Gothwal H et al [37](2011)	Fourier-NN	98.48
Jadhav[38](2012)	ANNs	86.67
In this study (2013)	MLP BPA	93.72
in this study (2013)	AMMLP	**98.25**

Table 4: Classification accuracies obtained with our method and other classifiers from the literature.

In this paper we use 11 descriptors in the input layer of the AMMLP without applying a feature selection method. Despite the complexity of our training phase, we have achieved our goal of convergence in a minimal time.
The test stage also shows that this method is an interesting combination of speed, reliability and simplicity, the obtaining results show clearly that this approach can be an interesting alternative in the case of unbalanced data (number of N and V beats are much greater than R and L beats).

VII. CONCLUSION

In this study, the Artificial Metaplasticity in a MLP has been applied to the problem of cardiac arrhythmias classification. The AMMLP approach is based on the biological property of metaplasticity. The goal of this research was to compare the accuracy of the proposed AMMLP with the classical MLP using Backpropagation algorithm and also with other classifiers cited in state-of-the-art. We have used the MIT-BIH Database to evaluate our algorithm. We noticed that the proposed AMMLP classifier provides better results than classical MLP. From the above results, we conclude that the AMMLP obtains very promising results in classifying different cardiac arrhythmias. We believe that the proposed system can be very helpful to the physicians for their as a second opinion for their final decision. By using such an efficient tool, they can make very accurate decisions. Our AMMLP classifier, proved to be equal or superior to the state-of-the-art algorithms applied to MIT-BIH Database.

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