Design of an Artificial Neural Network and Feature Extraction to Identify Arrhythmias from ECG

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***Abstract*—This paper presents a design of an artificial neural network (ANN) and feature extraction methods to identify two types of arrhythmias in datasets obtained through electrocardiography (ECG) signals, namely arrhythmia dataset (AD) and supraventricular arrhythmia dataset (SAD). No special ANN toolkit was used; instead, each neuron and necessary calculus were modeled and individually programmed. Thus, four temporal-based features are used: heart rate (HR), R-peaks root mean square (R-RMS), RR-peaks variance (RR-VAR), and QSR-complex standard deviation (QSR-SD). The network architecture presents four neurons in the input layer, eight in hidden layer and an output layer with two neurons. The proposed classification method uses the MIT–BIH Dataset (Massachusetts Institute of Technology–Beth Israel Hospital) for training, validation and execution or test phases. Preliminary results show the high efficiency of the proposed ANN design and its classification method, reaching accuracies between 98.76% and 98.91%, when in the identification of NSRD and arrhythmic ECG; and accuracies of 86.37% (AD) and 76.35% (SAD), when analyzing only classifications between both arrhythmias.**

Keywords—arrhythmia identification; pattern recognition; signal analysis; artificial neural network.

I. INTRODUCTION

Electrocardiography (ECG) is an important non-invasive technique used in medicine to observe the heart variation and abnormalities over a period of time. Continuous and typical ECG signal consists of P-waves, QRS-complexes and T-waves [1], and provides fundamental information about the electrical activity of the heart. Abnormalities in this electrical activity may represent heart diseases defined by the absence of any structural cardiac defects and are responsible for a large number of sudden, unexpected deaths, including those of young individuals [2]. Thus, several diseases may be detected through ECG analysis such as, atrial fibrillation (AF) [3,4], long QT syndrome, Brugada syndrome, catecholaminergic polymorphic ventricular tachycardia and the short QT syndrome [2] and arrhythmia [5]. Some of these diseases cannot be visually distinguished easily by a medical specialist due to its similar appearance with other signals [6]. However, a deep computational analysis may be used to detect small differences and possible diseases. To allow for such automatic detection, several features may be extracted from ECG signals such as, heart rate variability (HRV) triangular index [7], morphological features [8] through the temporal-domain analysis [7,9] and frequency-domain [1,7,10], and wavelet transform coefficients [11,12,13,14]. Furthermore, automatic methods to correctively identify diseases or patterns from these signals may be reached through statistical Markov models [15], artificial neural networks (ANN) [1,3,6,16], linear discriminant analysis [17], and support vector machine (SVM) [18].

Arrhythmia is defined as a general term for an irregularity or rapidity of the heartbeat or an abnormal heart rhythm [4]. Arrhythmias can initiate or exacerbate acute systolic heart failure in patients with pre-existing heart disease [19]. Therefore, studies in arrhythmias characteristics, definition and consequences are explored in several works.

Leren et al., investigated early markers of arrhythmic events and improved risk stratification in early arrhythmogenic right ventricular cardiomyopathy, performing resting and signal averaged ECG [5]. Farwell et al., presents a paper review about the current clinical and molecular understanding of the electrical diseases of the heart associated with sudden cardiac death [2]. Kohno et al., presents a state-of-the-art about the relation between atrial arrhythmias and pacing-induced rhythms disorders, inside the context of cardiac implanted devices [20]. Gopinathannair et al., exposed the arrhythmia-induced cardiomyopathies (AIC) showing its definition, potential reversible condition and aspects [19].

In the arrhythmia identification context, other works present classifications and methods used. Caswell et al. used new techniques to analyze arrhythmia through morphology of the ECG waveform with success in correctly detecting fatal arrhythmias through waveform correlation analysis of intracardiac electrograms. They also defined a two-dimensional feature space with linear decision boundaries using a least squares minimum distance classifier [21]. Povinelli et al., proposed a novel, nonlinear, phase space based method to quickly and accurately identify life-threatening arrhythmias, determined for six different ECG signal lengths [22]. Artis et al. used ANNs to identify AF, using the MIT-BIH Dataset, with each AF and non-AF recordings with 15-min [3]. Shadmand and Mashoufi, developed a new personalized ECG signal classification using ANN variant named block-based neural network (BBNN) and then classify ECG heartbeats, possibly also detecting arrhythmia patterns [6]. Lin, proposed a method for heartbeat identification from ECG using ANN and grey relational analysis (GRA) to classify cardiac arrhythmias patterns [1].

This paper presents a new approach to identify two types of arrhythmias patterns from ECG signals: the arrhythmia dataset (AD) and the supraventricular arrhythmia dataset (SAD), Moreover, are used four temporal-based features: heart rate (HR), R-peaks Root Mean Square (R-RMS), RR-peaks

variance (RR-VAR), and QSR-complex Standard Deviation (QSR-SD).

The MIT-BIH Arrhythmia Dataset is used as reference to training, validation and test or execution phases for the ANN.

II. DATASET

For processing (features extraction) and classify arrhythmia patterns from ECG this paper uses MIT–BIH (Massachusetts Institute of Technology–Beth Israel Hospital) Dataset. It provides the ECG signals and is used during training, validation, and execution of the ANN classifier. The ECG classes/databases considered are:

- Normal sinus rhythm database (NSRD);
- Arrhythmia database (AD);
- Supraventricular Arrhythmia database (SAD).

This dataset uses time-date in seconds, grid interval x-axis of 0.2 seconds, grid interval y-axis of 0.5 mV, and standard data format. It consists of 240 NSRD instances, 432 AD instances, and 252 SAD instances.

Table I presents each class used during training, validation, and execution phases.

TABLE I. DATASET CLASSES FOR EACH ANN PHASE.

MIT-BIH Dataset			
Classes/Phases	**Training**	**Validation**	**Execution**
Normal (NSRD)	162	54	24
Arrhythmias (AD)	207	69	156
Suprav. Arrhyt. (SAD)	117	39	96
Total instances	486	162	276

III. METHODOLOGY

In the training, validation and execution or test phases, 67 ECG signals (large-signals) with one hour duration from MIT-BIH Dataset are used. Each large-signal is divided in 12 short-signals with duration t_s (5-min), number of R-peaks N_p, and signal length L_p, resulting in 648 (54×12) short-signals, where 486 (75%) are used in the training phase and 162 (25%) for the validation phase.

Furthermore, according to the literature, 5-min recording for each signal is an appropriated option for a minimal and reliable ECG analysis [7], although other researchers use 15-min recording [3] or more.

A. Signal Processing

ECG signals include noise. Then, signal processing (or pre-processing) was developed to enables the ECG signals to be used in the ANN inputs.

This processing includes signal samplings, low pass Butterworth filter, data smoothing Savitzky–Golay filter, FFT transform and baseline wander.

This steps were applied to remove noises, give support in the RR-peaks identification and to maintain the baseline signals (i.e. same signal reference) during the signal processing executed before the feature extraction process, as shown in Fig. 1.

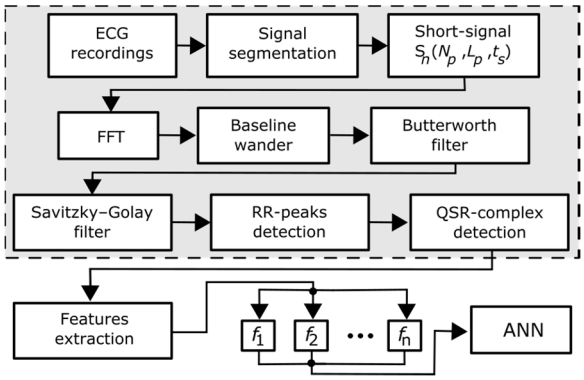

Fig. 1. Steps of signal processing (in gray) applied in the ECG dataset signals to derive the ANN inputs.

1) Filtering and Frequency-domain

Once the dataset is chosen, the filtering and noise reduction are the next steps of signal processing to guarantee higher accuracy in the feature extraction phase. After the already described signal segmentation to allow for the short-signal descriptions, frequency is investigated. Power spectrum variations are observed between 0 and 20 Hz in frequency domain similarly to previous tests found in the literature [1].

Fast Fourier Transform (FFT) is used to determine that frequency spectrum with signal sampling frequency of 500 Hz and average of 54,166 samples to each short-signal.

The QSR-complex is a very important part from ECG and it varies for both normal and abnormal rhythms. Thus, this paper also uses this identification as a feature to the ANN inputs vector.

B. Features Extraction

Feature extraction is applied in training, validation and execution phases. Thus, from each short-signal, the signal processing returns four temporal-based features:

- Beats per minutes or heart rate (HR);
- R-peaks root mean square (R-RMS);
- QSR-complex standard deviation (QSR-SD);
- RR-peaks variance (RR-VAR).

1) Time-domain Features

The temporal-based (time-domain) feature extraction starts with R-peaks detection algorithm to obtain the HR. Equation 1 represents each short-signal in minutes, where $\Delta p_{(m+1)} = (p_{m+1} - p_m)$; p_m and p_{m+1} represent consecutives R-peaks positions inside the set $\wp = \{p_1, p_2, .., p_{N_p}\}$ of all R-peaks positions from a short-signal. The correspondent R-peaks or QSR-complex values are represented by the set $\vartheta = \left\{\vartheta(p_1 \; or \; q_1), \vartheta(p_2 \; or \; q_2), .., \vartheta(p_{N_p} \; or \; q_{N_p})\right\}$.

$$t_s = \frac{60}{L} \sum_{m=1}^{N_p - 1} \Delta p_{(m+1)} \quad (1)$$

Once the R-peaks are detected, the HR feature is calculated using Eq. 2, where t_s is the reference time for the short-signal,

N_{p_t} represents the total amount of R-peaks on minute t, t_f is the final minute from the short-signal, and $\Delta p'_{(m+1)}$ and p'_n, represent $\Delta p_{(m+1)}$ and p_n in minutes, respectively.

$$hr = \frac{\sum_{t=1}^{t_f}\sum_{n=1}^{N_{p_t}} p'_n}{\sum_{m=1}^{N_p-1}\Delta p'_{(m+1)}} = \frac{1}{t_s}\sum_{t=1}^{t_f}\sum_{n=1}^{N_{p_t}} p'_n \quad (2)$$

The R-RMS feature is a generalized mean (Eq. 3) based in the R-peaks values set ϑ, and the signal length L_p starting from the first to the last R-peak from S_n.

$$rms = \sqrt{\frac{1}{L_p}\sum_{n=1}^{N_p}|\vartheta(p'_n)|} \quad (3)$$

The QSR-SD feature uses R-peaks as a reference to find QRS-complexes thus, it is based in R-peaks values from set ϑ (Eq. 4). Furthermore, the standard deviation for each QSR-complex from the set $\wp_{qsr} = \{q_1, q_2, .., q_{N_p}\}$.

$$std_{QSR} = \sqrt{\frac{1}{L_p-1}\sum_{n=1}^{N_p}|\vartheta(q'_n) - \mu|^2} \quad (4)$$

Finally, the RR-VAR feature (σ^2) also uses R-peaks positions (Eq. 5), where μ represents the mean of each short-signal S_n.

$$var = \sigma^2 = \frac{1}{L_p-1}\sum_{n=1}^{L_p}|p'_n - \mu|^2 \quad (5)$$

2) *Feature-Classification Memory*

All extracted features f (represented by the set $\mathcal{F} = \{f_1(n), f_2(n), f_3(n), f_4(n)\}$) and classification results $c(n)$, are co-related in the set with size N_c (number of memory's instances) that is,

$$\mathcal{M} = \{\mathcal{F}(f_i(n)|_{i=1}^{I}), c(n)\}\,|_{n=1}^{N_c} \quad (6)$$

where $\mathcal{M}$ represents the classifier's memory, i.e., all data learned during the training and validation phases. Therefore, it includes the stored features f_i and its correspondent stored classification $c(n)$ at iteration$n$.

C. *Artificial Neural Network*

Artificial neural networks are one of most powerful tools for diagnosing diseases in an automatic manner [6]. Thus, an ANN architecture is proposed in this work, with four input neurons, eight hidden neurons (based in two hidden layers) and two output neurons (i.e. $4 \times 4 \times 4 \times 2$ network), as shown Fig. 2.

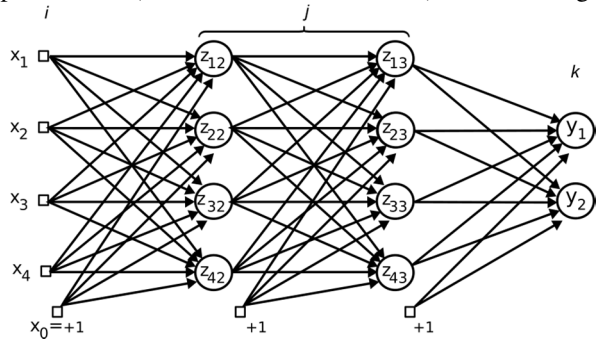

Fig. 2. ANN architecture. Input layer (*i*), hidden layers (*j*) and output layer (*k*).

Each input is represented by $\{x_1, x_2, x_3, x_4\}$, and during the ANN training and validation phases, these inputs are defined by,

$$X_{train} = \begin{bmatrix} x_{1(1)} & x_{2(1)} & x_{3(1)} & x_{4(1)} \\ x_{1(2)} & x_{2(2)} & x_{3(2)} & x_{4(2)} \\ \vdots & \vdots & \vdots & \vdots \\ x_{1(486)} & x_{2(486)} & x_{3(486)} & x_{4(486)} \end{bmatrix} \quad (7)$$

$$X_{valid} = \begin{bmatrix} x_{1(1)} & x_{2(1)} & x_{3(1)} & x_{4(1)} \\ x_{1(2)} & x_{2(2)} & x_{3(2)} & x_{4(2)} \\ \vdots & \vdots & \vdots & \vdots \\ x_{1(162)} & x_{2(162)} & x_{3(162)} & x_{4(162)} \end{bmatrix} \quad (8)$$

D. *Classification*

Classification uses four features and memory ($\mathcal{M}$) resource to accurately identify arrhythmia patterns. Beyond ANN, K-nearest neighbors (K-NN), is also used as a memory seeker at execution phase. Thus, arrhythmia identification/classification is based in three phases, such as:

- **Training**: uses 75% from dataset to train the network to have best weights as possible;
- **Validation**: uses 25% from dataset to validate the training results;
- **Execution or Test**: uses new data to indeed identify arrhythmias patterns from ECG signals, comparing previous classifications from the memory, with new data.

Our pattern identification uses the ANN multilayer perceptron (MLP-ANN) with backpropagation algorithm. Furthermore, no special ANN toolkit was used; instead, each neuron and necessary calculus were modeled and individually programmed. Therefore, the configuration variables i.e., *momentum* (α) and *learning-rate* (η), are adjusted during the training phase using the training set (Eq. 9):

$$\mathcal{T} = \{x(n), d(n)\}|_{n=1}^{N} \quad (9)$$

where $\mathcal{T}$ includes the stimulus $x(n)$ applied to input layer to reach $d(n)$, that represents the desired output from network at iteration n.

The network weights (w^*) and biases (b^*) are also included in output nodes and are defined as bellow.

$$w^* = \begin{bmatrix} w_{1(1)} & w_{1(2)} & w_{1(3)} \\ w_{2(1)} & w_{2(2)} & w_{2(3)} \\ & \vdots & \\ w_{16(1)} & w_{16(2)} & x_{16(3)} \end{bmatrix} \quad (10)$$

$$b^* = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \\ b_{41} & b_{42} & b_{43} \end{bmatrix} \quad (11)$$

The ANN uses the *induced local field* (forward computation), as represented by Eq. 12, where x_i goes to input to neuron (node) j and w_{ji} $d$enotes a connection from neuron j to i.

$$v_j(n) = \sum_{i=1}^{m} w_{ji}(n)x_i(n), j \geq 1 \quad (12)$$

The network also uses the sigmoidal activation function given by Eq. 13.

$$\varphi_j\left(v_j(n)\right) = \frac{1}{1+exp\left(-av_j(n)\right)}, a > 0 \quad (13)$$

Furthermore, the *error signal* or *instantaneous error* produced by output layer of each neuron *j* is defined by Eq. 14,

$$e_j(n) = d_j(n) - y_k(n) \quad (14)$$

where $d_j(n)$ represents the *j*th element of $d(n)$ and $y_k(n)$ the *k*th instantaneous output. Furthermore, the $y_k(n)$ and the *instantaneous error energy* (ξ) of each neuron *j* (Eq. 15) are both considered to reach best network accuracy along epochs (iterations) [23, 24].

$$\xi_j(n) = \frac{1}{2}e_j^2(n) \quad (15)$$

The *local gradient* applied to neuron *k* located in the output layer, is described by Eq. 16,

$$\delta_k(n) = e_k(n)y_k(1 - y_k) \quad (16)$$

and the ANN weights adjustments (backward computation) applied to each output neuron, is defined by *delta-rule* (Eq. 17) [23, 24],

$$\Delta w_{kj}(n) = \alpha\Delta w_{kj}(n-1) + \eta\delta_k(n)y_k(n) \quad (17)$$

where the *momentum* α ($[0;1]$) is used to avoid instabilities while increasing the *learning-rate* η ($[0;1]$).

1) Network Output

The network returns two outputs $\{y_1, y_2\}$ in binary format, giving 2^2 different classification outputs as shown in Eq. 18.

$$Y = \begin{bmatrix} y_{1(1)} & y_{2(1)} \\ y_{1(2)} & y_{2(2)} \\ \vdots & \vdots \\ y_{1(648)} & y_{2(648)} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \\ \vdots & \vdots \\ 0 & 1 \end{bmatrix} \quad (18)$$

The output patterns are: “Not defined” or not classified, when the classifier does not match the output either as normal or arrhythmic pattern; “SAD” when matching supraventricular arrhythmia; “NSRD” when matching to normal cardiac rhythm pattern; and “AD” when matching to arrhythmic pattern, as demonstrated bellow.

$$\begin{bmatrix} 0 & 0 \\ 0 & 1 \\ 1 & 0 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} "Not\ defined" \\ "SAD" \\ "NSRD" \\ "AD" \end{bmatrix} \quad (19)$$

2) Execution or Test Phase

This phase uses, mainly, new instances from the dataset, according Table I from Section II (Dataset).

To compare the extracted feature from each new short-signal, the K-NN algorithm is used to seek the best classification already stored in memory ($\mathcal{M}$) during the training and validation phases. Thus, this algorithm uses Euclidian distance measurement to find the smallest distance between the stored features in $\mathcal{F}$, and the new feature vector $\mathcal{F}^* = \{f_1^*(n), f_2^*(n), f_3^*(n), f_4^*(n),\}$ that can be extracted from MIT-BIH Dataset, as described in Eq. 20,

$$\ell(n) = \sqrt{\sum_{i=1}^{4}(\mathcal{M}\{\mathcal{F}^*(f_i^*)\} - \mathcal{F}(f_i(n)))^2} \quad (20)$$

where f_i^* is constant. Finally, the iteration n^*, representing the smallest $\ell(n)$, determines the classification result in the execution phase, i.e., $c(n^*)$ represents the final classification given by the presented ANN.

Figure 3 shows a summary of all steps for the developed approach.

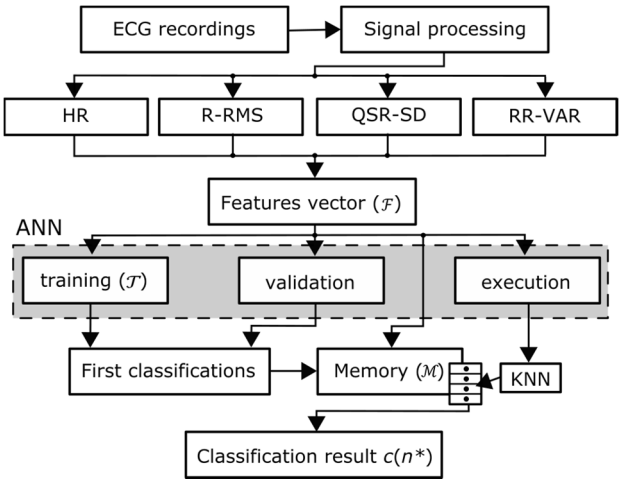

Fig. 3. General view of all processes of arrhythmia classification since the ECG recordings dataset until final classification $c(n^*)$.

IV. RESULTS

This work presents a design of an ANN classifier and features extraction methods to identify arrhythmia patterns. Hereinafter, uses the previously described MIT-BIH Dataset (Section II). To test the accuracy of the developed ANN, four steps are used: training, validation and two different executions.

In the execution phase, two different perspectives are used:

- Using the same set of features from the validation phase (25% from dataset), K-NN is applied to set of features from training, and classifications stored in memory $\mathcal{M}$;
- Using a new set of unused examples from the dataset, and K-NN applied to set of features from training, and classifications in $\mathcal{M}$.

A. Training and Validation Phases

During the training and validation phases were used 648 instances (i.e. 100% from considered dataset).

Figure 4 presents the four feature values along the input layer from the network during training phase. Note that in this case is applied 486 instances of the dataset (i.e. 75% of 648 instances).

Each plotted vertical segment represents different inputs between the NSRD, AD and SAD class instances. Furthermore,

the features QSR-SD and RR-VAR were multiplied by 100 and 10,000 times respectively, due its small values.

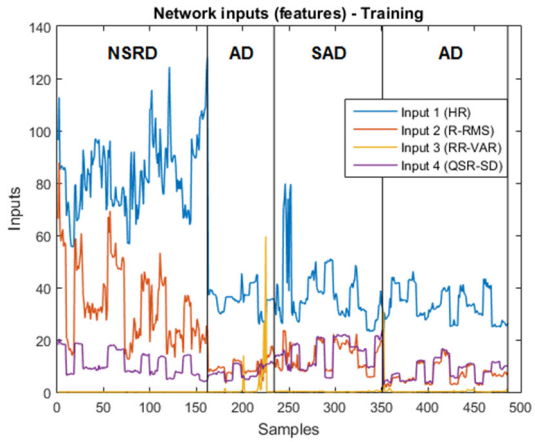

Fig. 4. Features values for the ANN input during training phase.

Figure 5 shows the variance (σ^2) feature applied to ANN during training phase. Note that AD and SAD segments present more spikes when compared to NSRD segment. It occurs because in cases of arrhythmia, the R-R peaks distances (intervals) become more irregular.

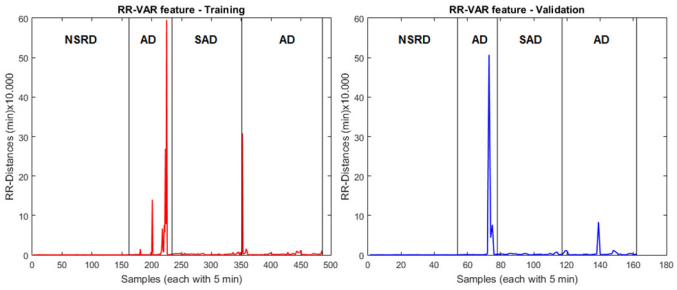

Fig. 5. Input feature RR-VAR based in R-peaks variance (σ^2) applied during training phase.

The outputs from each neuron are presented in Fig. 6. Note that, during training and validation phases, the ANN outputs return results very similar to the desired output.

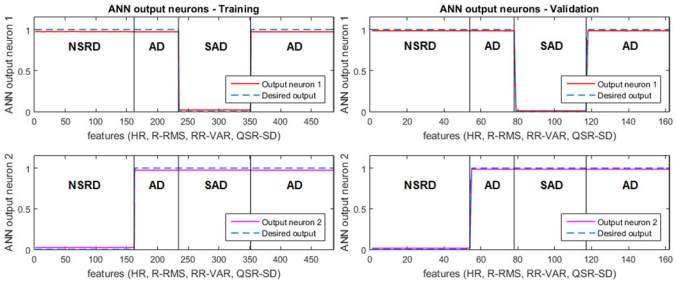

Fig. 6. ANN outputs during the training and validation phases using $\alpha = 0.2$, $\eta = 0.40$, $a = 2$.

All errors produced by ANN neurons, such as squared errors and sum of errors, are shown in Fig. 7.

Note that, close to 400 iterations (epochs) the output errors are normalized, stabilizing the network accuracy to returns correctly the arrhythmias classification.

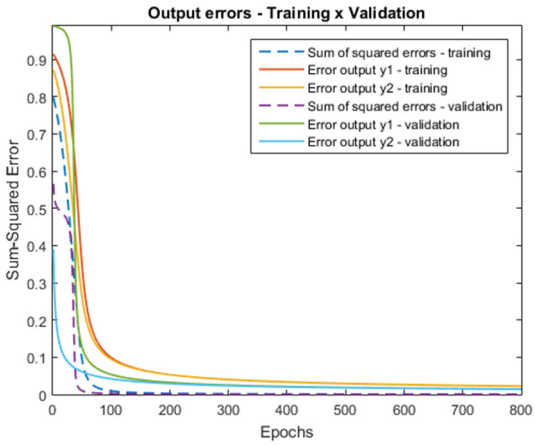

Fig. 7. Example of the ANN output errors during the training and validation phases using $\alpha = 1$, $\eta = 0.55$, $a = 2$.

Figure 8 presents final clustering reached by classifier, showing the relation between HR (horizontal axis) and R-RMS (vertical axis) features. Note the complex non-linearity classification reached during training and validation phases for all 684 instances (486 for training and 162 for validation) from MIT-BIH Dataset.

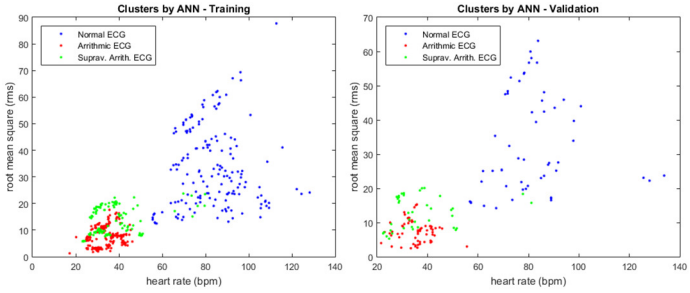

Fig. 8. Correct identification of normal ECGs and arrhythmias, during training and validation phases, using $\alpha = 1$, $\eta = 0.55$, $a = 2$.

B. *Execution Phase using Features from Validation*

In this execution phase of arrhythmia identification, the algorithm shows high accuracy (98.76%) when using the validation features (i.e. 25% of 648) from MIT-BIH Dataset.

Table II presents the confusion matrix for the classification results during execution phase after the K-NN algorithm using the feature-classification memory ($\mathcal{M}$) from training. Thus, considering the classification between a normal ECG (NSRD) and arrhythmic ECG (AD+SAD), the classification reached an accuracy of 98.76% (2 errors over 162 instances). Furthermore, considering only Normal (NSRD), Arrhythmia (AD) and Supraventricular Arrhythmia (SAD), the accuracies are of 96.26% (2 mistakes between arrhythmias), 97.10% (2 mistakes between arrhythmias) and 92.30% (3 mistakes between arrhythmias), respectively.

TABLE II. CONFUSION MATRIX FOR TWO ARRHYTHMIA IDENTIFICATION.

Actual/Predicted	NSRD	AD	SAD	Total
NSRD	52 (**96.29%**)	0	2	54
AD	0	67 (**97.10%**)	2	69
SAD	0	3	36 (**92.30%**)	39

C. Execution Phase with New Features-Set

In this execution or test phase of arrhythmia identification, the algorithm stills presents high accuracy of 98.91% even when using a new set of examples.

Table III presents the confusion matrix for the classification results. Therefore, considering the classification between NSRD and all arrhythmic ECGs (AD+SAD), the accuracy reached 98.91% (3 errors over 276 instances). Furthermore, considering NSRD, AD and SAD, the accuracies reached were 100.00% (no errors), 75.64% (3 errors and 35 mistakes between arrhythmias) and 60.41% (38 mistakes between arrhythmias), respectively.

TABLE III. CONFUSION MATRIX FOR TWO ARRHYTHMIA IDENTIFICATION.

Actual/Predicted	NSRD	AD	SAD	Total
NSRD	24 (**100.0%**)	0	0	24
AD	3	118 (**75.64%**)	35	156
SAD	0	38	58 (**60.41%**)	96

V. CONCLUSIONS AND FUTURE WORKS

This paper presents a design of an ANN to identify two different arrhythmias patterns from ECG. Also is presented an ANN with support of K-NN method and the MIT-BIH Dataset. Finally, the effectiveness for the accurate identification of arrhythmias patterns is established.

Thus, the designed and implemented ANN model reach accuracies between 98.76% and 98.91%, identifying NSRD and arrhythmias (AD+SAD) patterns; and reach accuracies with mean values of 86.37% (AD) and 76.35% (SAD), when only arrhythmias are analyzed, i.e. when there are classification mistakes between both arrhythmias patterns.

In future works, we intend to use the same ANN concept with more neurons in hidden layers and other input features (e.g. time and frequency domain features), i.e. wavelets transform coefficients or mel-frequency cepstrum coefficients (MFCC) to solves different problems inside of the cardiac arrhythmia context and other area such as emotion recognition based in speech emotion recognition and/or biosignal emotion recognition.

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