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CLASSIFICATION OF HEART RHYTHM DYNAMICS USING ARTIFICIAL NEURAL NETWORKS

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Abstract. *Biological rhythms represent one of the most important manifestations of natural systems and therefore, dynamical analysis can establish relations among responses characteristics and biological functioning. Artificial intelligence developments are motivating automatic systems capable of performing cardiac diagnosis for medical support. This work aims to develop an intelligent system based on artificial neural networks capable of classifying cardiac rhythms from the heart rate variability (HRV) signal extracted from electrocardiograms. Five cardiac rhythms are selected for the analysis: normal sinus rhythm; atrial fibrillation; sinus bradycardia; premature ventricular contraction; and ventricular tachyarrhythmia. Linear and nonlinear features are employed to feed the artificial neural network, which is analyzed considering different arrangement of input configurations. After the definition of the neural network, clinical cases are analyzed showing satisfactory results, being able to classify the heart rhythm of patients with the same diagnosis offered by cardiologists.*

Keywords: *Nonlinear dynamics, artificial intelligence, heart rate variability, ECG, cardiovascular rhythms.*

1. INTRODUCTION

Life and its physiological aspects can be understood from a dynamical perspective. On this basis, biological rhythms can be defined as regular or irregular, associated with physiological or pathological functionalities. Some examples of regular dynamics that represent a healthy behavior are menstrual cycles and sleep routines. On the other hand, neurological tics, tremors, and epilepsy can be classified as pathological periodic dynamics. Additionally, irregular rhythms can also reflect diseases such as cardiac arrhythmias like fibrillation and various neurological disorders (Savi, 2005).

The study of the cardiovascular system has evolved over the years due to its importance to life. The heart is the essential organ of the cardiovascular system, responsible for supplying blood and oxygen to all parts of the body. Its anatomy is characterized by two halves, each composed of two chambers. The heart is situated in the thoracic cavity, surrounded by a membrane filled with fluid known as the pericardium. The cardiac muscle produces electrical impulses that cause the contraction of the heart, which is responsible for pumping blood throughout the entire body.

Despite its apparent regularity, heart rhythm is characterized by some irregularity, known as *heart rate variability* (HRV). HRV is a measure that indicates the variation in the time between consecutive heartbeats, also referred as the RR interval, since it is related to the distance of the R waves in the electrocardiogram (ECG) (Taye et al., 2019). HRV is a nonlinear and non-stationary signal that represents the autonomous activity of the nervous system and its influence on the cardiovascular system (Asl et al., 2008). Additionally, HRV has been analyzed to quantify its characteristics using three methods of analysis: time domain, frequency domain, and nonlinear.

The HRV signal was clinically used for the first time by Hon and Lee (1965), who noticed that fetal distress was accompanied by changes in the variability of their heartbeats, even before any changes could be detected (Reed et al., 2005). In 1970, HRV measurement was used as a marker for diabetic neuropathy (Murray et al., 1970). Wolf et al. (1978) demonstrated that patients with reduced heart rate following a myocardial infarction had a higher mortality rate, indicating that HRV is an accurate predictor of mortality after a heart attack. Decades later, HRV alterations were found in various patients with different cardiovascular conditions, highlighting its relevance for the detection and diagnosis of heart diseases (Reed et al., 2005).

HR has been extensively investigated as a tool capable of predicting the risk of death from cardiac pathologies. However, a recurring problem in HRV measurement is accurately locating the peaks of the R waves in electrocardiograms. This task requires a robust R-wave detector algorithm. The higher the accuracy of the R-wave detector is, the lower is the error in analyzing the HRV spectrum. An unidentified R-wave can cause a larger error than a detected R-wave in the wrong position (Aydin et al., 2016).

Despite all the precautions taken during the medical exam, an electrocardiogram recording in a clinical environment can be contaminated by several factors such as: electrical interference from surrounding equipment or effects from the power supply; analog-to-digital signal conversion; patient's muscular movement (Dotsinsky, 2007).

Nonlinear dynamics perspective allows one to define the main characteristics of cardiac rhythms, and their various parameters can be used to characterize a cardiac signal as physiological or pathological (Anuradha and Reedy, 2008). HRV dynamical analysis can reveal abnormal patterns, being identified by RR intervals.

Automation in medical expert systems primarily aims to build an intelligent system capable of automatically detecting diseases, whether to indicate their occurrences or classify them. Advances in the field of artificial intelligence, as presented in Sanjana et al. (2020), have enabled the automation of medical expert systems. Since most of sudden deaths caused by cardiac diseases are due to ventricular arrhythmias, anticipating the occurrence of these arrhythmias is important for saving patients (Ebrahimzadeh et al., 2014). In this regard, there is a huge motivation for the use of machine learning techniques for the recognition of heart diseases.

Artificial intelligence can be defined as the theory and development of computer systems capable of performing tasks that require intelligence. Machine learning is a subfield of artificial intelligence that is based on data optimization techniques, providing a set of mathematical methods for extracting meaningful features from data. Data mining and clustering the data into distinct and meaningful patterns can be exploited for decision-making (Brunton and Kutz, 2017).

Linear discriminant analysis, Bayesian decision-making, decision trees, and extreme machine learning are some examples of machine learning techniques, but the most commonly used for classification is the artificial neural networks (ANN) and support vector machines (Asl et al., 2008). Artificial neural networks (ANN) are capable of identifying and classifying distinct classes to assist in the analysis and diagnosis of heart health (Brunton and Kutz, 2017).

Anuradha and Reddy (2008) presented a method capable of accurately classifying cardiac arrhythmias by combining wavelets and artificial neural networks (ANN). Sanjana et al. (2020) proposed the method of transfer learning to interpret features learned by the model to detect different types of heart diseases. In this method, the model was trained on a specific tachycardia called atrial fibrillation and tested with other diseases such as ventricular fibrillation and sinus tachycardia. Asl et al. (2008) presented a classification algorithm for cardiac arrhythmias using heart rate variability (HRV).

This work presents an artificial neural network capable of identifying and classifying cardiac rhythms based on the heart rate variability of the electrocardiograms. Nonlinear and linear tools are employed to extract signal features that are used as input parameters. Different cardiac rhythms characterized by electrocardiograms (ECGs) extracted from the PhysioNet's repository of real data are used to investigate a collection of rhythms that include normal sinus rhythm (NSR), ventricular tachyarrhythmia (VT), atrial fibrillation (AF), premature ventricular contraction (PVC), and sinus bradycardia (SB). HRV signals composed of 16 RR intervals and 32 RR intervals are of concern. After the definition of the network configuration, it is employed to classify cardiac rhythms of real patients.

2. CARDIAC SYSTEM AND HRV SIGNAL

The heart is a continuously working muscle, and its electrical system is responsible for controlling cardiac activities and pumping blood to the rest of the body. This electrical system is also referred as the conduction system. Each heartbeat is generated by an electrical signal in the cardiac muscle, commanded by the vagus nerve, along with contributions from the sympathetic trunk, being responsible for influencing heart rate, cardiac output, and heart contraction forces. The autonomic nervous system is divided into two distinct components: the sympathetic and parasympathetic (vagal) components, which act directly on the heart in an antagonistic manner, stimulating or inhibiting its activity (Goldberger, 2000; Dário et al., 2016).

Each heartbeat begins with an electrical signal originating from the sinoatrial (SA) node located in the right atrium. Cardiac rhythms are defined by the electrical activity of the heart originating from three components:

- Sinoatrial (SA) node, which is the heart's natural pacemaker, possesses special cells that generate electricity through chemical reactions, causing the heart to contract and expand.
- Atrioventricular (AV) node, which establishes the connection between the atria and ventricles through which electrical signals are conducted.
- His-Purkinje (HP) system, which transmits the electrical signals through the ventricles contracting them. This system includes the following components: the His Bundle, where the system initiates; the right bundle branch, which refers to the branching of the system to the right; the left bundle branch, which refers to the branching of the system to the left; and the Purkinje fibers, where the system terminates.

Figure 1, left, shows the position of each of these elements in the heart electrical conduction system. Figure 1, right, displays the waves generated by their activities, showing a typical electrocardiogram (ECG). Note that the interval between the peaks represented by the R waves, denoted as the RR interval, characterizes the heart rate variability (HRV).

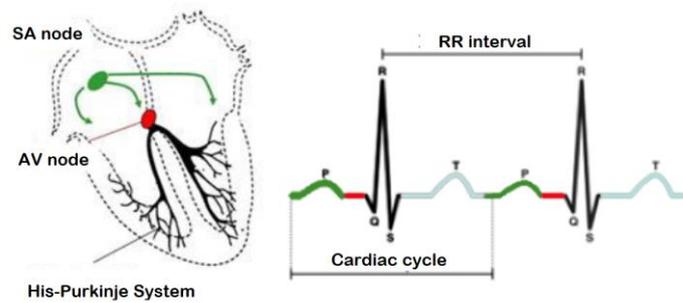


Figure 1. Electrical conduction system of the heart, curves of the ECG and RR interval.

3. DATABASE AND SIGNAL CHARACTERIZATION

This work utilizes time series data from the PhysioNet repository (Goldberger et al., 2000), which contains databases from various research studies. The heart rate variability (HRV) data is generated from electrocardiogram (ECG) signals provided by the MIT-BIH Arrhythmia and Atrial Fibrillation databases from the Massachusetts Institute of Technology and Beth Israel Deaconess Medical Center, as well as the Creighton University Ventricular Tachyarrhythmia database.

Each recording in the MIT-BIH Arrhythmia database has a duration of slightly over 30 minutes (Moody, 1997). The MIT-BIH Atrial Fibrillation database includes 25 ECG recordings of patients with atrial fibrillation, each one with 10 hours (Moody and Roger, 2000). The Creighton University Ventricular Tachyarrhythmia database includes 35 minutes of ECG recordings of patients experiencing episodes of ventricular tachycardia and ventricular fibrillation (Physionet, 2007). Due to their comprehensive signals and free availability to the public, the PhysioNet data present are used in this work.

Interval size for feature extraction is crucial to accurately characterize the signals according to the cardiac rhythm dynamics. Lian et al. (2011) presented a study in which they divided the ECGs into windows containing 32, 64, and 128 RR intervals to analyze the efficiency of atrial fibrillation identification. In this work, 5 cardiac conditions are analyzed and classified using signals with 32 RR intervals and 16 RR intervals. The HRV signal composed of RR intervals can be analyzed using both linear and nonlinear tools (Taye et al., 2019; Asl et al., 2008).

Linear features are part of the standard measures of HRV signals that are strongly recommended, especially according to the publication by the Task Force of the European Society of Cardiology and North American Society of Pacing and Electrophysiology in 1996. These features can be evaluated in the time and frequency domains. In this work, seven linear features were extracted in the time domain, divided into Direct Measurement of RR intervals and Measurement through differences between RR intervals.

Direct Measurement of RR Intervals:

RRm: Refers to the average value of 32 or 16 RR intervals.

SDNN: Refers to the standard deviation considering all 16 or 32 RR intervals.

Measurement through Differences between RR Intervals:

RMSSD: Refers to the square root of the mean squared differences between successive RR intervals.

SDSD: Refers to the standard deviation of the differences between successive RR intervals.

pNN50, pNN10, pNN5: These refer to the percentage of successive RR interval differences that differ by more than 50, 10, and 5 ms, respectively, divided by the total number of RR intervals (32 or 16).

Time domain linear parameters lack the ability to discriminate signals between the sympathetic and parasympathetic contents of the HRV signal. In this regard, frequency domain analysis has the ability to discriminate between these two components. The spectral density in the high-frequency (*HF*) band of 0.15-0.4 Hz of the HRV signal reflects the activity on the sinoatrial node, while the spectral density in the low-frequency (*LF*) band of 0.04-0.15 Hz is related to baroreceptor control, being mediated by both vagal and sympathetic activities. On this basis, the ratio between *LF* and *HF* spectral densities (*LF/HF*) is employed as a frequency domain feature of the HRV signal (Asl et al., 2008; Shaffer & Ginsberg, 2017; Billman, 2023; Shaffer et al., 2014).

Despite this type of analysis allows the assessment of sympathetic and parasympathetic activities, some authors pointed that this methodology has limitations under stress or physical exercise conditions once these situations increase the involvement of nonlinear organic subsystems in the electrocardiographic signal. Therefore, nonlinear tools are necessary (Neves et al., 2006).

Nonlinear phenomena are inherent of the HRV signals due to the complex interaction of hemodynamic, electrophysiological, and humoral variables, as well as the regulation of the central and autonomic nervous systems, as presented in the Task Force of the European Society of Cardiology and North American Society of Pacing and

Electrophysiology in 1996. HRV signal analysis based on nonlinear dynamics methods is capable of extracting valuable information for the physiological interpretation of heart rate variability and the assessment of the risk of sudden death.

Poincaré maps have showing to be a powerful tool to characterize changes in the RR intervals trends. By considering the HRV signal as a time series of RR intervals, it is possible to build a map based on two subsequent R peaks. ($RR_i - RR_{i+1}$) (Asl et al., 2008). On this basis, the Poincaré map of the heart rate variability analysis is a nonlinear tool that can be employed to the values of each pair of RR intervals. Note that a signal without rate variability would be represented by a single point and, irregularity is represented by a dispersion around this point. Figure 2 shows the Poincaré map for different heart rhythms.

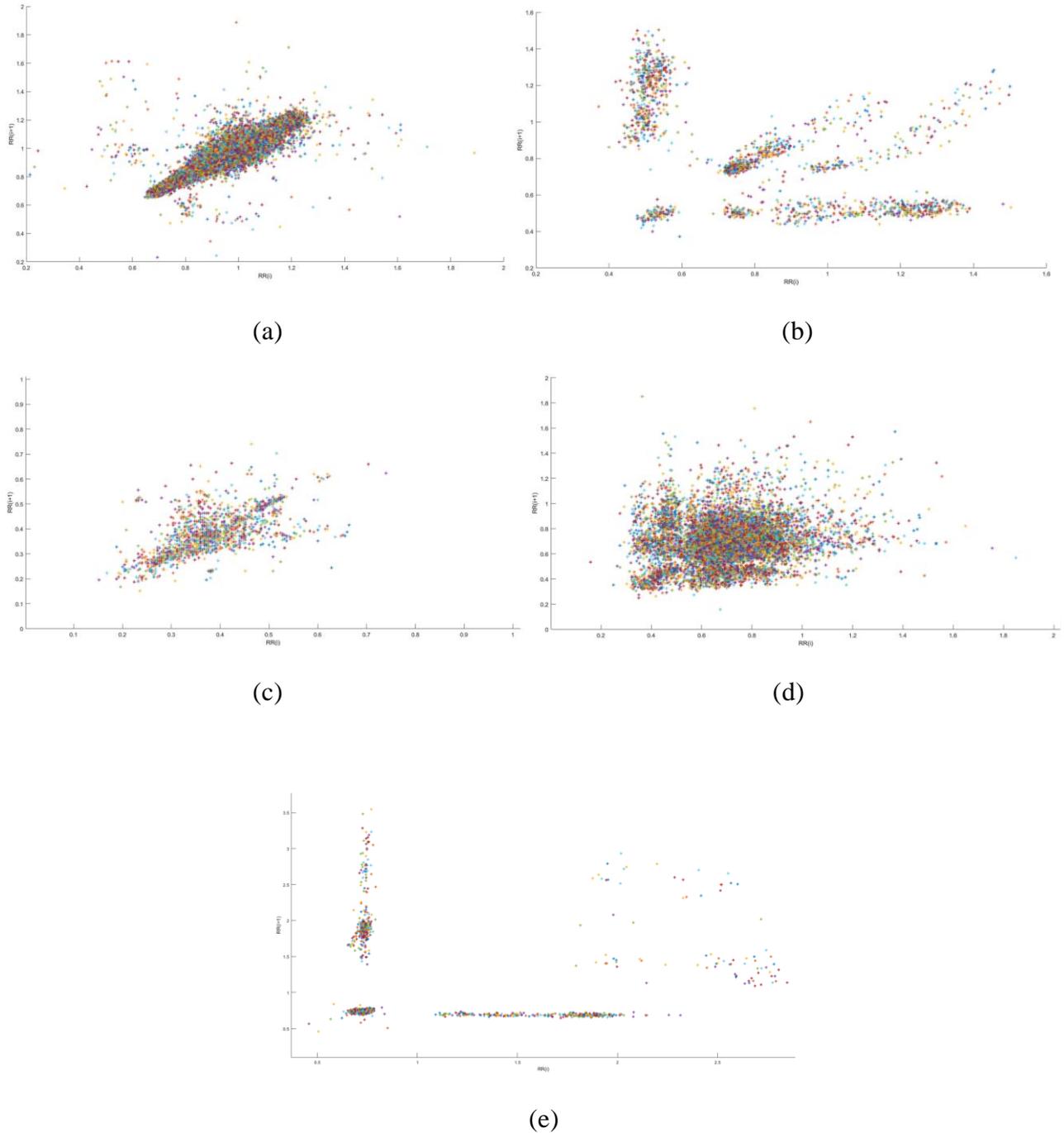


Figure 2. Poincaré maps for different heart rhythms: (a) normal sinus rhythm; (b) premature ventricular contraction; (c) ventricular tachyarrhythmia; (d) atrial fibrillation; (e) sinus bradycardia.

Poincaré maps can be quantitatively analyzed by different parameters (Taye et al., 2019): *SD1* represents the rapid beat-to-beat variation, while *SD2* describes the long-term variability in the HRV signal. The ratio *SD1/SD2* describes the relationship between these two components, being an interesting feed the neural network.

On this basis, 9 characteristics are extracted from the HRV signals to feed the artificial neural network discussed in the next section.

4. ARTIFICIAL NEURAL NETWORK

Consider a multilayer perceptron neural network of a feedforward type, which involves sequential layers composed of neurons with activation functions. Each layer generates a set of vectors that serve as input to the next layer, which is another set of functions. There are three types of layers: input, output, and hidden layers. Figure 7 presents a typical neural network of this type.

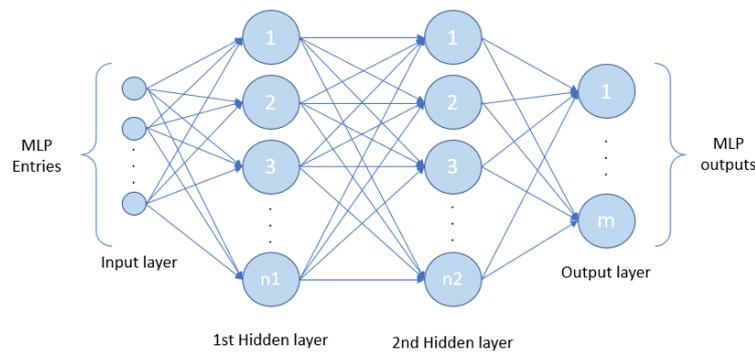


Figure 7. Multilayer perceptron diagram.

The activating is provided by a nonlinear sigmoid function, as expressed in the Eq. (1). This choice is supported by Brunton and Kutz (2017), who identified greater flexibility in dealing with nonlinear relationships.

$$f(x) = \frac{1}{1 + e^{-x}} \quad (1)$$

The neurons in the output layer, on the other hand, utilize the softmax transfer function, which is commonly employed in multiclass classification problems. The softmax function is unbounded and maps a real-valued input to an output between 0 and 1, and the outputs for each input vector sum up to 1,

$$f(x) = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}} \quad (2)$$

By choice, 70% of the collected data is used to train the network, 15% to validate it, and 15% to test it in a supervised manner. Gradient descent training techniques is employed together with backpropagation (Ogier, 2021). Table 1 presents the distribution of data used for training, validation, and testing of the neural network.

Table 1. Network data.

	Dataset							
	16 RR intervals				32 RR intervals			
	Number of Characteristics Vectors	Train (70%)	Validation (15%)	Test (15%)	Number of Characteristics Vectors	Train (70%)	Validation (15%)	Test (15%)
NSR	974	682	146	146	487	341	73	73
PVC	109	76	16	16	54	38	8	8
VT	111	78	17	17	55	39	8	8
AF	566	396	85	85	283	198	42	42
SB	107	75	16	16	53	37	8	8

The configuration of the artificial neural network is built with three layers (Figure 8): the input layer composed of 9 neurons; the hidden layer with 7 neurons; and the output layer composed by 5 neurons. It is important to establish a proper definition of the hidden layer. Using too few neurons can result in underfitting, where the model is unable to capture the complexity of the data. On the other hand, too many neurons can lead to overfitting, where the model becomes overly fitted to the training examples that performs poorly on new data (Brunton and Kutz, 2017).

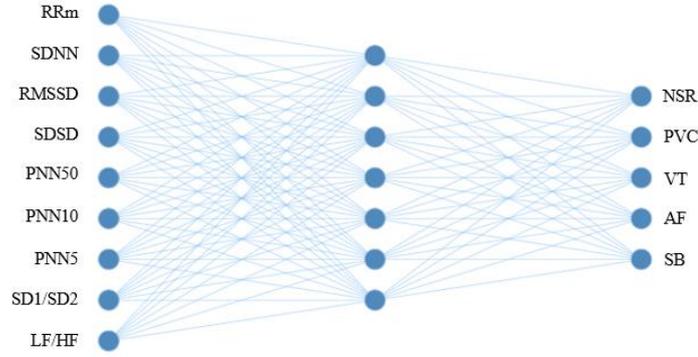


Figure 8. Artificial neural network architecture.

Network evaluation is performed by considering confusion matrices, a table that represents performance metrics. It identifies the true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), being useful for measuring accuracy, sensitivity, precision, and specificity. Accuracy represents the percentage of elements correctly classified (positives or negatives) and provides an overall measure of model performance. The formula for *accuracy* is given by

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

Precision, also known as positive predictive value, measures the proportion of patients correctly identified as having a specific cardiac condition out of all patients diagnosed with that condition. It focuses on the accuracy of positive predictions. The formula for precision can be seen in Eq. (4).

$$Precision = \frac{TP}{TP + FP} \quad (4)$$

Recall, also known as sensitivity or true positive rate, measures the proportion of patients with a specific cardiac condition who were correctly identified as having that condition. It focuses on the ability to correctly detect positive cases,

$$Recall = \frac{TP}{TP + FN} \quad (6)$$

Score *F1* combines precision and recall into a single measure, being the harmonic mean between precision and recall, providing a balanced evaluation of the model's performance,

$$F1 = \frac{2}{Recall^{-1} + Precision^{-1}} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (5)$$

Specificity is the percentage of true negative samples correctly identified out of the total negative samples. It represents the model's ability to correctly identify negative cases

$$Specificity = \frac{TN}{TN + FP} \quad (6)$$

5. RESULTS AND DISCUSSIONS

This section presents the analysis of the artificial neural network applied to heart rhythms. The analysis is based on signals signals composed of 16 RR intervals and 32 RR. Results are extracted from the confusion matrices and summarized Table 2. It is noticeable the good performance for all rhythms. It is observed that the network fed with

smaller signals achieves superior results compared to the network fed with larger signals when evaluating the network ability to accurately detect ventricular tachyarrhythmia. For this reason, this network is used to diagnose six patients, once ventricular tachyarrhythmia is considered one of the most dangerous arrhythmias due to its potential to rapidly evolve into ventricular fibrillation, which can be fatal if not diagnosed and defibrillated promptly.

Table 2. Artificial neural network analysis.

		Positive Predictive Value		Recall (Sensitivity)		Score F1		Specificity		Accuracy		Error rate	
		16 RR	32 RR	16 RR	32 RR	16 RR	32 RR	16 RR	32 RR	16 RR	32 RR	16 RR	32 RR
Rhythm	N	98.6%	95.5%	100.0%	100.0%	99.3%	97.7%	98.4%	96.0%	95.4%	97.1%	4.6%	2.9%
	PVC	100.0%	100.0%	54.5%	62.5%	70.6%	76.9%	100.0%	100.0%				
	VT	92.9%	90.9%	100.0%	100.0%	96.3%	95.2%	99.6%	99.2%				
	AF	90.9%	100.0%	96.4%	97.9%	93.6%	98.9%	95.9%	100.0%				
	SB	88.9%	100.0%	100.0%	100.0%	94.1%	100.0%	99.2%	100.0%				

Six clinical cases are now considered to evaluate the proposed artificial neural network. The patients' cardiac rhythms are classified based on the diagnosis provided by cardiologists, and their diagnoses are compared to the classification offered by the neural network. Results can be seen in Table 3, which includes information such as age, gender, used medications, cardiologist's diagnosis, and neural network's diagnosis, respectively. It should be pointed out that the neural network provides exactly the same diagnosis offered by the cardiologists.

Table 3. Clinical analysis comparing the diagnosis offered by cardiologists and the neural network.

Clinical case	Age	Gender	Medicines	Cardiologist's diagnosis	Classification by artificial neural network
1	24	Female	None	NSR	NSR
2	68	Male	None	NSR	NSR
3	No info	No info	No info	VT	VT
4	84	Male	Hydrochlorothiazide and Lasix®	AF	AF
5	24	Female	Antihypertensive	PVC	PVC
6	76	Female	Metildopa	SB	SB

6. FINAL REMARKS

The identification and classification of cardiac rhythms is essential and the adoption of intelligent automatic systems is an interesting approach to help clinical activities. This system needs to be capable of providing reliable cardiac diagnosis supporting medical teams.

An artificial neural network is employed to build this support system, being capable to identify and classify different cardiac rhythms satisfactorily. Five rhythms are of concern considering HRV signals extracted from ECGs: normal sinus rhythm, premature ventricular contractions, ventricular tachyarrhythmia, atrial fibrillation, and sinus bradycardia.

Linear features in the time domain and frequency domain, and nonlinear feature represented by Poincaré map are extracted from the HRV signals. Accuracy, precision, sensitivity, F1 score, and specificity metrics are evaluated for two scenarios: one with the network being fed with larger signals, consisting of 32 RR intervals, and another with the network being fed with smaller signals, consisting of 16 RR intervals.

Results show that the network achieved good efficiency in identifying and classifying cardiac rhythms for both 16 or 32 RR intervals. Nevertheless, the network working with 32 RR intervals showed slightly better performance. Despite this, results of the network with 16 intervals are also satisfactory.

The analysis of 6 clinical cases involving different individuals with different ages and cardiac conditions are carried out considering the artificial neural network fed with smaller signals, with 16 RR intervals. Results are satisfactory, being identical to the cardiologist analyses, demonstrating that the network is capable of diagnosing patients. The authors believe that this intelligent system has an interesting potential to help cardiac diagnosis giving support for identification and classification of cardiac rhythms.

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