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Abstract— **The main objective of this paper is to prepare a Clinical Decision Support System (CDSS) for a multi-class classification of ElectroCardioGram (ECG) signals into certain cardiac diseases. This CDSS is based on Artificial Neural Network (ANN) as a machine learning classifier and uses time scale input features. Fourty eight (48) ECG signals were selected from MIT-BIH arrhythmia database, of one minute recording. Unfortunately, among several types of learning algorithms for the ANN classifier, finding the appropriate one demands a comparative study. So, in this study, we have evaluated the impact of two learning algorithms, which are the Levenberg-Marquardt (trainlm) and the Bayesian-Regularization (trainbr) on the proposed ANN performance. Consequently, we have achieved that trainbr reaches the most accurate result (93.8%), while trainlm generates the highest classification speed (0.582s). Subsequently, in order to assess the efficiency of this work, a second comparative study with related works, is done. Therefore, despite not being in the same working conditions, the obtained accuracy (93.8%) is considered acceptable.**

Keywords—component; machine learning; ECG; Arrhythmias; Neural Networks.

I. INTRODUCTION

The electrical activity of the heart muscle is represented by the Electrocardiogram (ECG) waveform. In fact, the ECG consists of five successive waves called P, Q, R, S, and T respectively. Fig. 1 represents a normal ECG signal, where the P wave represents atrial depolarization, the QRS complex represents the ventricular depolarization and T wave represents the ventricular repolarization [1]. By the way, ECG plays an important role in monitoring and diagnosing patients. In fact, it is mainly used to detect various arrhythmias. So, when the ECG is regular and atrial depolarization is followed by ventricular depolarization, the ECG heart beat is considered Normal. However, when it becomes irregular, the ECG heart beat is considered in a case of arrhythmia. However, diagnosing manually the ECG signal is difficult and time consuming task.

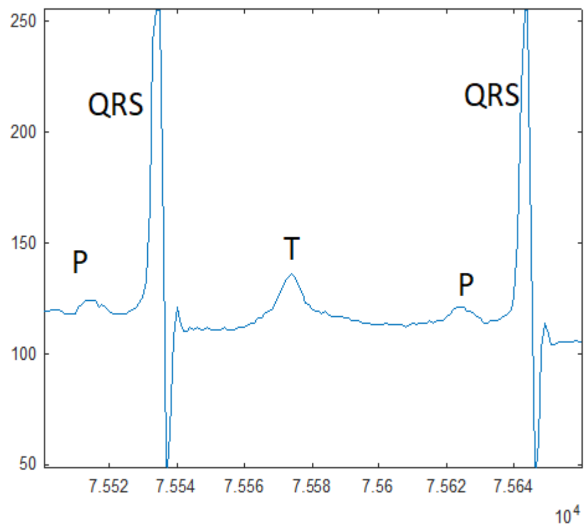

Fig. 1. Normal ECG signal.

Hence, the use of a Clinical Decision Support System (CDSS) is recommended for cardiologists, since it is developed to aid them to make efficient decision in a quick time. Indeed, building CDSS necessities the employment of the artificial intelligent classifiers based on machine learning algorithms. These algorithms detect automatically meaningful patterns by referring to past experience, without any external assistance from human being [2]. As a result, in order to improve the performance results of the CDSS, plenty researchers have proposed various machine learning algorithms, such as the Neural Networks [3], the fuzzy logic methods [4], the Neuro Fuzzy logic Networks [5] and many others [6]. However, although researchers have the same purpose, each researcher has used his proper methodology in

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pre-processing the ECG signal. Therefore, various ECG arrhythmia classification models are investigated [7, 8, 9, 10].

In the same reason, this paper deals with the classification of ECG signals into five different class, using ANN ,as a machine learning classifier for classification, and Discrete Wavelet transformer (DWT) coefficients for feature extraction. So, a fitting neural function (fitnet) based on a feed-forward neural network, is studied. The fitnet is applied mainly to classify 48 ECG signals of one minute recording, into Normal class (N), Paced class (P), Left Bundle Branch Block class (LBBB), Right Bundle Branch Block class (RBBB) and Premature Ventricular Contraction class (PVC) [11]. However selecting the appropriate training algorithm for the neural network (fitnet), needs a comparison study. Indeed, two training algorithms are applied and subsequently a comparison study between them is done. This study focusses mainly on the accuracy and the time classification obtained by using the two training algorithm. Moreover, to evaluate the efficiency of the proposed multi-class classification model, another comparison study with related works is presented. This paper is organized as follows. In section II, we present the adopted methodology. Then, we start by introducing MIT-BIH arrhythmia database as well as ECG feature extraction stage. In section III, we detail the fitting neural function classifier and two training algorithms: the Levenberg-Marquardt (trainlm) and the Bayesian regularization (trainbr). In section IV, we present the main results obtained using trainlm and trainbr by computing the Mean Square Error (MSE), the Accuracy (ACC), the Sensibility (Se), the Specificity (Sp), the classification error rate (CER) and the classification speed (Cl_speed), performances. Then, a brief comparison between the two training algorithms performances is done. After that, a comparative analysis between the proposed work and other related works is also examined. Finally, a conclusion and some perspectives related to this research topic are given in section V.

II. METHODOLOGY

This study is done in order to prepare a CDSS for a multi-class cardiac arrhythmia classification. In fact, the CDSS will be able to classify ECG signal into one of five pre-defined ECG categories (N, P, LBBB, RBBB and PVC). Thus, two main stages are coupled as it is described in Fig. 2. The first one is the ECG feature extraction which outcomes a representation of the input data into a set of feature [12] which are thereafter usable for the second stage called machine learning classification. In this paper, we have applied a fitnet neural function classifier. In this section, we will begin by introducing the ECG arrhythmia database as well as the ECG feature extraction approach.

A. Database

The MIT-BIH Arrhythmia Database of ECG waveforms, has been utilized in this work [13]. It is obtained from the website physionet.org. This database includes 48 files of 30 minutes recording. It covers approximately 109,000 beat labels. Its ECG waveforms are represented by a text header file, a binary file and a binary annotation file. The header files include the detailed information about the ECG signals such as sample numbers, sampling frequency, format type, and number of leads, patients' history, etc. [13].

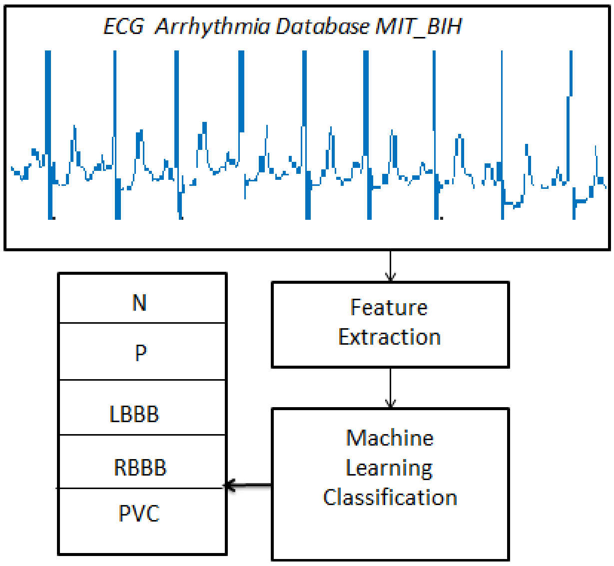

Fig.2. ECG arrhythmia classification methodology.

We have used all the ECG signals of only one minute recordings. As it is listed in TABLE I., these ECG recordings were categorized according to five types of beats (N, P, LBBB, RBBB and PVC).

TABLE I. DISTRIBUTION OF MIT-BIH DATABASE RECORDS.

ECG class	MIT_BIH ECG Recording
Normal	100, 101, 103, 105,106,108, 112, 113,114, 115, 116, 117, 121,122, 123, 201, 202, 203, 205, 209, 210, 213, 215, 219, 220, 221, 222, 223, 228, 230, 232, 234.
Paced	102, 104, 107, 217.
LBBB	109, 111, 207, 214.
RBBB	118, 124, 212, 231.
PVC	119, 200, 208, 233.

B. Feature Extraction

By following the cardiologists' arrhythmia classification practice, many types of features can be extracted from the ECG waveform in several ways. In this study, as it is a non-stationary signal, time-scale coefficients are employed to extract its features [14]. Indeed, Wavelet Transform (WT) is applied to extract two types of features: morphological and coefficients of DWT. The first type groups the morphological features and the second type sets the Discrete Wavelet Transformer (DWT) coefficients.

1) ECG Morphological Features: We have practiced wavedet algorithm developed in ECG_kit toolbox [15], compatible with MATLAB to extract from ECG signal some morphological features such as ECG peaks (P, Q, R, S, T), time duration between waves (PR, QT, PT, ST, QRS and RR) and number of beat per minute (bpm) [15]. Then, the maximum values of peaks, the standard deviation (std) of time duration between waves and the mean as well as the std of the bpm, were computed. We have obtained 14 morphological features for each ECG signal.

2) ECG DWT Features: We have chosen the Daubechies (db) wavelet of order 6 since it has similar morphological shape of the ECG signal [15]. Then, we have applied 8 decomposition levels for each heartbeat. Therefore, we have returned for each ECG signal 16 coefficients (8 approximations and 8 details). Nevertheless, we have selected the mean, the standard deviation and the variance of each approximation and detail coefficient [15]. Hence, for each ECG signal, we have obtained 48 DWT.

In total 62 features are extracted from the ECG signal which are the sum of 48 DWT coefficients and 14 morphological features.

III. CLASSIFICATION

After the feature extraction stage, a supervised Artificial Neural Network classifier is considered. It is the fitting neural function. This ANN learns from a set of features, five ECG beat types (N, P, LBBB, RBBB and PVC).

A. The Fitting Neural Function

The standard architecture of the fitting neural function is similar to a feed forward neural network. It consists of three layers: input layer, hidden layer, and output layer [16]. The input layer represents the feature vector where each feature is attached to a neuron through a weight value [16]. Then, features are multiplied by their corresponding weight. After that, they are summed in the hidden layer. Then, they are directed to a transfer activation function (purelin, hardlim, sigmoid, logistic) in the output layer, in order to give each neuron, its class which has to be classified.

However, based on how fitnet adapts the network parameters (weights and biases) to decrease the error between the output and target values, several types of Backpropagation training algorithms, are available [17]. In this work, two training algorithms (trainbr and trainlm) have been assessed for the fitnet model.

B. The Levenberg-Marquardt training algorithm

The Levenberg-Marquardt (trainlm) training algorithm belongs to Quasi-Newton algorithms which perform the second derivative of the performance function, without computing the Hessian matrix [18]. Therefore, trainlm updates an approximate Hessian matrix in each iteration of the algorithm. Hence, as it has not to compute the Hessian matrix, trainlm is considered as the fast training algorithm for networks of moderate size. However, it requires a lot of memory and computation storage [18].

C. The Bayesian Regularization Training Algorithm

The Bayesian Regularization training algorithm (trainbr) is a modified algorithm of the Levenberg-Marquardt training method. It is developed for reducing the memory used by the trainlm optimization algorithm. It minimizes a combination of squared errors and weights, and then determines the correct combination to get the best generalization of the network [18].

For both of the training algorithms (trainbr and trainlm), the training stops for several occurred conditions such as the maximum number of repetitions is reached, the performance is minimized to the goal or the time has been surpassed.

IV. EXPERIMENTAL STUDY AND RESULTS

The experimental results were carried out in MATLAB software package 17.a. In this experiment, MIT_BIH arrhythmia database is used. In fact, forty eight (48) ECG signals, of one minute recordings, are selected for classifying the ECG signal data into five classes (N, P, LBBB, RBBB and PVC). Two types of features, which are the morphological and the DWT coefficients, are extracted. Further they are classified using the fitnet classifier. In this study, the fitnet consists of 62 neurones in the input layer, 5 neurones in the output layer and 10 neurones in the hidden layer, which were determined empirically. The fitnet uses the sigmoid and suturing linear transfer functions in the hidden and output layers respectively.

The input dataset (62x 48) is divided into training and testing set in the ratio of 70% and 30% respectively. In this work, our target matrix has 5 rows and 48 columns. Its elements are binary values. Each output class is different from each other's by keeping 1 to the proper cell in which signal belongs while other elements are 0s. Hence the binary target values (1,0,0,0,0), (0,1,0,0,0), (0,0,1,0,0), (0,0,0,1,0) and (0,0,0,0,1) are assigned to 'N' class, 'P' class, 'LBBB' class, 'RBBB class and 'PVC' class, respectively.

Concerning the training algorithm of the fitnet classifier, two algorithms, which are trainlm and trainbr , are evaluated. Thus, to evaluate the classifier, based on the mutually exclusive categories recognition of TP (True Positive), FP (False Positive), TN (True Negative), FN (False Negative), four statistical performance metrics (Se, Sp, ACC, CER,) are employed. They are defined in the equations (1), (2), (3) and (4) respectively. The MSE and the Cl_speed, which are defined in the last two equations (5) and (6), are also used to evaluate the classifier.

$$Se = 100x\frac{TP}{TP+FN} \tag{1}$$

$$Sp = 100x\frac{TN}{TN+FP} \tag{2}$$

$$ACC = 100x\frac{TP+TN}{TP+FN+TN+FP} \tag{3}$$

$$CER = 100x\frac{FP+FN}{TP+FN+TN+FP} \tag{4}$$

$$MSE = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=0}^{\mathrm{N}} (\mathrm{t_i} - \mathrm{o_i})^2 \tag{5}$$

Where N is the total number of input vectors, t_i is the target vector, o_i is the output vector.

$$Cl\_speed = (training\_time + testing\_time) \quad (6)$$

Where training _time and testing _time are the amount of time spent for training and testing the network, respectively.

Hence, two comparative studies are done. The first one consists on comparing the two training algorithms (trainlm and trainbr) according to the obtained performance metrics (Se, Sp, CER, CL_speed, MSE and ACC). However, the second one consists on comparing the obtained ACC of the proposed work to some other related works, applying the ANN and DWT features.

A. Comparative Study between Two Training Algorithms

This comparative study focuses mainly on the impact of the selected training algorithm on the ANN performances. Therefore, the obtained results using trainlm and trainbr training algorithms are revealed in TABLE II. In fact, it summarizes the computing of the Se, the SP, the CER, and the ACC with respect to the mutually exclusive categories (TP, FP, TN and FN). Besides, it shows the obtained MSE and Cl_speed.

On the first hand, it can be seen that the total number of correct classification (TP values) is equal to 42 and 45 out of 48 ECG signal, using trainlm and trainbr respectively . As a result, the trainbr training algorithm achieves the most accurate result (93.8%) and the lowest MSE (0.027). However, trainlm is speeder (0.582s) than trainbr (12.292s). On the other hand, by using trainbr training algorithm, the minimum CER (0.0%) was obtained for two classes (LBBB and RBBB). While by using trainlm, the minimum CER is obtained for only one class (LBBB). Besides, the worst CER (10.41%) is obtained for the 'N' class, by using trainlm .

However, whatever the training algorithm, for LBBB, RBBB and PVC, the Se and Sp performances are almost similar. Whereas, considering the 'N' class, the Sp (93.4%) and the CER (6.25%) obtained using trainbr are better than those (82.3%, 10.41) obtained using trainlm.

As a summary, the most accurate results are achieved by employing trainbr learning algorithm (93.8%) while the rapidest (0.582s) result is obtained by applying trainlm learning algorithm. Consequently, since the selection of the desired ANN structure depends on criteria demanded by the experts who will use the CDSS, then the CDSS will use trainlm, if experts want a rapider result and trainbr, if they want the more accurate result.

B. Comparative Analysis with Related Works

In order to assess the efficiency of this work, a second comparative study with related works, is done. The study is summarized in TABLE III., which recapitulates the accuracy obtained by the proposed work and other classifiers, who apply ANN as a machine learning model and use DWT features [7, 8, 9, 10]. Consequently, these classifiers including the proposed work are effective to the tune of about 98.7%-93.8 % accuracy. In fact, as it shown in TABLE III , each research has used its proper methodology mainly in pre-processing the ECG signal (Extracted Features). Therefore, referring to TABLEIII, we have concluded that despite not being in the same working conditions as the others, the proposed method is considered as an acceptable method with 93.8% accuracy. In fact, in our case of study, we have used all the ECG signals from MIT-BIH database and we have considered all the obtained details and approximations. So, any feature selection method is applied. Contrary, other classifiers have selected the ECG signals from the input database as well as the DWT coefficients [8, 9, 10] and have applied different statistics over the DWT features. Hence, referring to TABLE III two main deductions are surveyed.

On the one side, for a fair comparison, several working conditions have to be considered, such as, the choice of the database, the duration of ECG recordings, the number of classes to be classified, the applied mother wavelet and its number of decomposition, the size and the statistics used over the DWT features and many others.

On the other side, the accuracy of the machine learning methods depends mostly on the pre-processing stage, such as the size and the quality of the training set which contains the extracted features.

TABLE II. CLASSIFICATION PERFORMANCE RESULTS USING TRAINLM AND TRAINBR.

Training algorithms	Beat types	TN	FP	FN	TP	Se (%)	Sp (%)	CER(%)	ACC (%)	MSE	Cl_speed (s)
trainbr	N	14	1	2	31	93.9	93.4	6.25	93.8	0.027	12.292
	P	44	2	0	2	100	95.6	4.16			
	LBBB	44	0	0	4	100	100	0.0			
	RBBB	44	0	0	4	100	100	0.0			
	PVC	43	0	1	4	80	100	2.08			
trainlm	Normal	14	3	2	29	93.5	82.3	10.41	87.5	0.066	0.582
	Paced	44	3	0	1	100	93.6	6.25			
	LBBB	44	0	0	4	100	100	0.0			
	RBBB	43	0	1	4	80	100	2.08			
	PVC	41	0	3	4	57.1	100	6.25			

TABLE III. COMPARATIVE ANALYSIS WITH RELATED WORKS.

Reference	Database	Class	Extracted Features		ACC (%)
			Mother wavelet/number of decomposition	***Selected features & Statistics used***	
[7]	The first 3 minutes of 48 ECG recordings from the MIT-BIH database.	Five classes (N, P, LBBB, RBBB and PVC)	(db2/5)[a]	- Maximum, Minimum, mean, and standard deviation of (D1..D5)[b] and (A5)[c]. -Power, kurtosis, skewness and timing information, extracted from the QRS complex. Total: 28 features.	96.7
[8]	The 549 ECG records from Physionet bank.	Three classes (N,Myocardial Infraction and others).	db3/5	- Standard deviation of (D1 .. D5 and A5). Total: 6 features.	98.72
[9]	The minute of 12 ECG recordings from the MIT-BIH database .	Five classes (N, P, LBBB, RBBB and PVC)	db2/5	-Maximum ,Minimum , mean and the standard deviation of (D1 .. D5 and A5) Total: 24 features.	98.6
[10]	The 500 samples of 10 ECG recordings from the MIT-BIH database.	Three classes (Normal and two arrhythmias)	db6/8	-Maximum ,Minimum and variance of (D1..D8) Total :24 features.	96.5
Proposed work	The first 1 minute of 48 ECG recordings from the MIT-BIH database.	Five classes (N, P, LBBB, RBBB and PVC)	db6/8	-Mean, standard deviation and variance of ((D1..D8) and (A1..A8)). -Morphological features. Total:62 features	93.8

[a] (dbi/j): Daubechies number i with number j decomposition [b] (Di): The Detail number i [c](A) :The Approximation number i

V. CONCLUSION

In this work, a preparation of a CDSS is investigated, based on ANN as a machine learning approach and DWT features. This CDSS is assessed to classify ECG signals into five classes. Therefore, all the ECG signals from MITBIH database, of one minute recording were analyzed. However, the configuration of the ANN classifier, such as the selection of the appropriate neural network, requires a comparison study. Accordingly, a comparison study between two different learning algorithms (trailm and trainbr) is done. Hence, we have obtained that the ANN is more accurate by using trainbr training algorithm (93.8%), while it is rapider by using trainlm training algorithm (0.582s). Successively, in order to evaluate the efficiency of this work, a second comparative study with related works, is presented. Consequently, this study reveals that the proposed work has an acceptable performance (93.8%). Moreover, the accuracy of the classifier depends not only on the configuration of the ANN classifier but also on the use of the feature extraction and feature selection techniques. In other words, accuracy depends on the size and quality of the training set. As a perspective, a similar study applying a feature selection approach is required. Therefore, we envisage the use of the Fuzzy Logic and the Neuro-Fuzzy network for both of the selection and classification stages. Furthermore, an intelligent tool whish selects the appropriate machine learning according to the criteria demanded by the experts, is necessitated.

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