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A SPECIALIZED LEARNING FOR NEURAL CLASSIFICATION OF CARDIAC ARRHYTHMIAS

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ABSTRACT

Automatic detection and classification of cardiac arrhythmias from ECG signals is of considerable importance in critical care or operating room patient monitoring. By examining the sequence of events on the ECG, cardiologists are able to diagnose cardiac arrhythmias. We propose in this paper a method to accurately classify the heartbeat of ECG signals through the artificial neural networks (ANN) and a solution to reduce time spent by specialist on long time ECG registers visual inspection.

We develop two neural classifiers from a global classifier we implemented a specialized classifier obtained after a second on-line training based on brief patient-specific ECG data (specialization by patient).

Our results demonstrate that Specialized classifier provides significantly enhanced performance (sensitivity Se=93.5185% ; 100% ; 100% correct classification CC= 96.1956% ; 100% ; 95.1220%) compared to Global classifier (sensitivity Se= 64.1711% ; 34.6154% ; 40% correct classification CC=79.5419% ; 37.0975% ; 69.4495%) respectively for the classification of Premature ventricular contraction, Right and Left bundle branch block.

Keywords: *Specialization, Classification, Artificial Neural Network (ANN), Cardiac Arrhythmias, Online Training, MIT BIH Database.*

1 INTRODUCTION

In spite of the rapid development of pathological research and clinical technologies, cardiovascular diseases are still the number one killer: they cause one death out of three in the world [20]. Each year, there are an estimated seven million deaths around the world and more than 26% deaths in Algeria due to cardiac arrhythmias.

Most of them are sudden cardiac deaths after myocardial infarction and 90% of them are due essentially to cardiac arrhythmias. 20% of sudden cardiac arrhythmias deaths are caused by heart block or pause (bradycardia) and 80% are caused by ventricular fibrillation (VF), frequently initiated by ventricular tachycardia (VT).

The “massive heart attack” is generally considered as an unpredictable and unpreventable event. In spite of the effectiveness of the post-heart-attack treatment, a lot of patients die because heart attacks occur suddenly without a shred of warning.

Recent studies show that there are generally significant cardiovascular abnormal symptoms such as palpitations, faints, chest pain, shortness of breath etc., before the sudden occurrence of a heart attack. If these abnormal symptoms can be early detected and diagnosed, time is saved to prevent the occurrence of heart attack or to provide an efficient treatment in time. Therefore, 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.[9]

Our objective is to develop a system adapted to each patient, especially to real-time cardiac arrhythmias detection using the artificial neural network.

The ability of properly trained artificial neural networks to correctly classify and recognize patterns makes them particularly suitable for use in an expert system that aids in the interpretation of ECG signals.

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Computer tools can significatively reduce time spent by specialists on longtime ECG registers visual inspection time.

The ECG waveforms may be differ for the same patient to such extend that they are unlike to each other and at the same time alike for different types of beats. This is the main reason that the arrhythmia beat classifier, which performs well for a given

ECG database, often fails when presented with another patient's ECG cycles.

In this paper, we present a new approach to beat recognition that is less sensitive to the morphological variation of the ECG . First, we develop a global neural classifier for a large ECG database. Then a short patient ECG record, annotated by a human expert, is needed to achieve a second online training of the global classifier in order to obtain a specialized classifier. These two classifiers are based on the backpropagation neural network algorithm.

2.BACKGROUND

Several algorithms have been described in the literature for detection and classification of ECG beats. The most difficult problem faced by today's automatic ECG analysis is the large variation in the morphologies of ECG waveforms, not only of different patients or patient groups but also within the same patient [5]. Various frameworks, related to heartbeat clustering, have been developed by statistical techniques where the decision boundaries are determined by the probability distributions of the patterns belonging to each class, which must either be specified or learnt [12]. Also, geometrical methods based on the minimum distance usually using Euclidean and Mahalanobis metric are commonly used [15], syntactic methods that use linguistic variables have been developed [10] and methods based on fuzzy logic have been considered[14]. However, the computational complexity is very high taking into account the large number of heartbeats[6].

This study presents a methodology based on Neural Networks to classify cardiac arrhythmias and after a second training during few minutes the classifier will be adapted to each patient.

3 MATERIALS AND METHODS

3.1 Ecg Holter

The ECG (electrocardiogram), the body-surface manifestation of the cardiac electrical potentials, is the most prescribed diagnostic measure in medicine and is routinely used to diagnose heart disease, to identify irregular cardiac rhythms (arrhythmias), to evaluate the effects of drugs, and to monitor surgical procedures. The magnitude, conduction, and duration of these potentials are detected by placing electrodes on the patient's skin. From the ECG tracing, the following information can be determined: Heart rate; Heart rhythm; Conduction abnormalities (abnormalities in the way the electrical impulse spreads across the heart); Coronary artery disease; Heart muscle abnormality ,etc. [16].

By examining the sequence of events on the ECG, cardiologists are able to diagnose cardiac arrhythmias. One of cardiac surveillance techniques based on ECG monitoring is the HOLTER monitoring.

HOLTER can be used to record 24hrs to 72hrs ECG signals with 1~3 leads in general. In HOLTER monitoring system, the ECG signals are processed later by dedicated software and then a diagnostic report will be created to aid cardiologists for further analysis.

3.2. Experimental Database

The MIT-BIH [13]Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG-Holter recordings, which were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range. The subjects were 25 men aged 32 to 89 years, and 22 women aged 23 to 89 years. In most records, the upper signal (first channel) is a modified limb lead II (MLII), obtained by placing the electrodes on the chest. The lower signal (second channel) is usually a modified lead V1 (occasionally V2 or V5, and in one instance V4); as for the upper signal, the electrodes are also placed on the chest. From 109871 annotated heartbeats (ECG beats examined by specialists), 1007 were selected for this study, which contain 4 different waveforms related to cardiac arrhythmias target. (see Table 1).

Label	Meaning
N	Normal beat
V	Premature ventricular contraction
R	Right bundle branch block
L	Left bundle branch block

Table1: Different waveforms

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3. 3 Data Preparation

Twenty two different patients, who have been considered in the experiments (taken from MIT-BIH), is shown in table 2.

We have limited the number of patients, taking part in the experiments, to provide at least different arrhythmia cases (N,V,R and L).

Records	(N)	(V)	(R)	(L)
Patient 100	62	0	0	0
Patient 101	5	0	0	0
Patient 103	58	0	0	0
Patient 105	10	0	0	0
Patient 106	27	34	0	0
Patient 109	0	0	0	104
Patient 111	0	0	0	41
Patient 113	6	0	0	0
Patient 115	10	0	0	0
Patient 116	45	0	0	0
Patient 118	0	0	12	0
Patient 119	50	34	0	0
Patient 122	5	0	0	0
Patient 123	5	0	0	0
Patient 124	0	0	33	0
Patient 200	0	25	0	0
Patient 203	0	15	0	0
Patient 207	0	0	0	40
Patient 208	0	152	0	0
Patient 212	5	0	26	0
Patient 214	0	50	0	50
Patient 215	103	0	0	0

Table 2: Evaluation data taken from the MIT-BIH database.

3.4. 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 ten features are defined in table 3 and figure 1.

In this study, we have divided our database in two sets: learning set and testing set.

These two sets were used simultaneously to develop the global classifier (to avoid over-fitting).
Then a few cycles of each selected record patient was used to develop the specialized classifier (patient specialization of the global classifier).

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

Table.3: The various descriptors

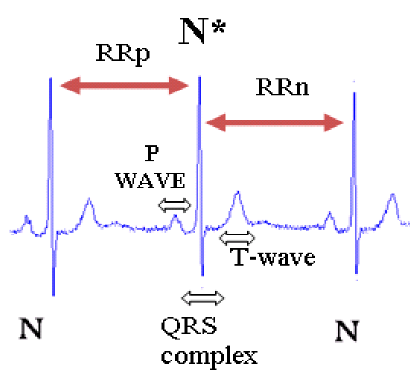

Figure1. Different waves of electrocardiogram detected by IMPE[1] (N*: Normal beat).

[1] program for the extraction of the different attributes

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3.4 Neural Network Classifier

Artificial neural networks (ANNs) are biologically inspired networks that are useful in application areas such as pattern recognition, classification etc.. The decision making process of the ANN is holistic, based on the features of input patterns, and is suitable for classification of biomedical data.

Typically, multilayer feed forward neural networks can be trained as non-linear classifiers using the generalized back propagation algorithm [17], [18], [1].

3.4.1 neural network classifier architecture

Each of the two neural classifiers (global and specialized) has a network of ten input neurons (Imposed by feature vector) and four output neurons. Each network is developed to output 1 for Normal beat, 2 for PVC beat ,3 for RBBB beat and 4 for LBBB beat, and it was trained by the backpropagation (BP) method. The BP algorithm is a supervised learning algorithm, in which a mean square error function is defined, and the learning process aims to reduce the overall system error to a minimum (less than 0.001). The activation function for each neuron was sigmoid.

The weights and the bias are initialized with a random numbers between -1 and 1.

The obtained networks for global and specialized classifiers have a hidden layer of three neurons.

3.5 The Learning Algorithms

During this work we used two main algorithms very traditional in nonlinear optimization.

1. The method of Quasi-Newton (Broyden Fletcher Goldfarb Shanno)[2],[7],[8],[19] , who is an alternative to conjugate gradient methods to rapidly optimize the parameters of weight.

2. The method of Levenberg-Marquardt(LM) [11], [4] .It is known to be the best algorithm for optimization problems. This method has a calculation time significantly higher than the method of Quasi-Newton.

By comparing several problems, it appears that none of these methods does a considerable advantage over the other. Each optimization method has advantages and disadvantages. Of course, no method does surely at least overall. It should therefore be placed in conditions where local minima are as few as possible or represent a sufficiently low error.

The training of the neural network ends if the sum of the square errors for all segments is less than 0.001 or the maximum number of training epochs is reached (500 epochs).

4. RESULTS & DISCUSSIONS

4.1 Global Classification

We have implemented 4 neural networks for classification, they are composed of different learning basis, presented in the following table (Table 4):

Neural network classifiers	Learning set
Classifier 1	103N, 200V, 118R, 207L
Classifier 2	119N, 214V , 212R , 109L
Classifier 3	116N, 203V , 124R , 111L
Classifier 4	215 N, 208V , 124R , 109L

Table 4: Neural classifiers used in this work.

103N:normal beat from the patient record 103 (MIT-BIH database).

103N ,119N ,116 N ,215N: correspond to Normal beat for each patient

200V, 214V ,203V ,208V: correspond to Premature ventricular contraction beat for each patient.

118R, 212R ,124R : correspond to Right bundle branch block beat for each patient.

207L , 109L ,111L: correspond to Left bundle branch block beat for each patient.

The learning of different networks is performed by two algorithms Quasi-Newton and Levenberg-Marquardt.

The implementation was experimented on a variety of datasets and results presented in figure.2 represent the performances.

To evaluate the performance of the proposed classifier, three measures are used and defined as follows:

$$\boldsymbol{Sensitivity}(\boldsymbol{Se}\%) = \frac{\boldsymbol{TP}}{\boldsymbol{TP}+\boldsymbol{FN}} \times 100$$

$$\boldsymbol{Specificity}(\boldsymbol{Sp}\%) = \frac{\boldsymbol{TN}}{\boldsymbol{TN}+\boldsymbol{FP}} \times 100$$

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$$Accuracy(Cc\%) = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

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.

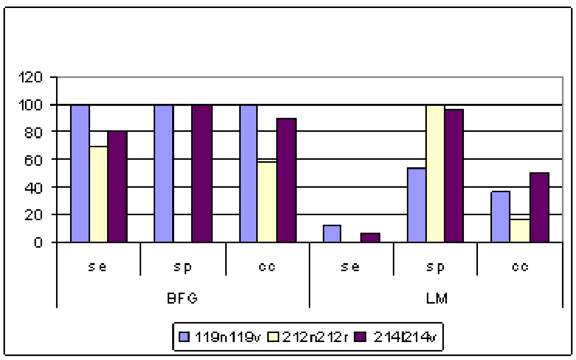

Figure 2: The performances of neural network 4 using BFG and LM training algorithms.

We used Different Test data for the evaluation of the classifier 4 training by the two algorithms.

Test data defined: 119n119v (arrhythmia target is V) , 212n212r (arrhythmia target is R), (arrhythmia target is L) .
The results, presented on Figure 2; show clearly that neural networks trained by the Quasi_Newton algorithm(BFG) performed better than neural networks trained by the Levenberg Marquardt algorithm(LM).

The performances of different networks across various test databases conducted us to choose Quasi_Newton(BFG) algorithm for the training of the specialized neural networks.
We developed in this work specialized classifiers for each patient from the best classifiers selected in the previous step.
We present in the next section the results of the specialization.

4.2 Specialized Classification

First, we develop a global neural classifier for a large ECG database (N, PVC'V 'RBB'R' and LBB'L'). Then a short patient ECG record , annotated by a human expert, is needed to achieve a second training of the global classifier in order to obtain a specialized classifier. These two classifiers, global and specialized, are based on the backpropagation neural network algorithm.

4.2.1. specialized learning for classification of 'pvc' (patient 106)

It is hoped that a global classifier recognize heart defects similar on different patients, but sometimes there may be failures, for this reason we adapt the global classifier on each patient.

The specialized classifier is initialized using the global neural network classifier which has been optimized offline, and it requires only little time to adapt it to a given patient.

We use the same architecture of global classifiers and specialized, except for the training of the specialized neural network ends if the sum of the square errors for all segments is less than 10^{-6} or the maximum number of training epochs is reached (500 epochs).

For the patient 106 we took the first 15beats ordered 8 beats 'N' and 7 beats 'V' of the patient 106 to specialize the various global networks defined in the tableau.3, and we test these specialized classifiers in the same patient 106. Test set is contains beats different to those used in the specialized training (106n106v).

Figure 3 and table 5 shows the results of classification of test data.

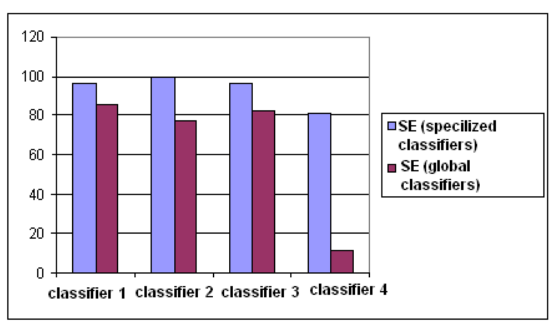

Figure 3: Comparison of sensitivity of the global and specialized classifiers.

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	Specialized classifiers			Global classifiers		
	Se	Sp	CC	Se	Sp	CC
Classifier 1	96.296	100	97.826	85.294	100	91.8033
Classifier 2	100	100	100	77.272	92.592	85.7143
Classifier 3	96.296	100	97.826	82.352	100	89.8305
Classifier 4	81.481	100	89.130	11.764	100	50.8197
Average	93.518	100	96.195	64.171	98.148	79.5419

Table5: Comparison of performances between the global and specialized classifiers.

The results presented in figure.3 show that the specialized classifier 2 correctly classified the target cases (premature ventricular contraction) resulting in a maximum sensitivity.

The specialized classifiers detect PVCs beats more accurately than global classifiers.

There is an increased ratio of classification and sensitivity of specialized classifiers compared to those of global classifiers.

4.2.3 specialized learning for classification of 'lbbb' (patient 214)

We specialize another patient 214 .the arrhythmia target is left bundle branch block ('L').learning set of the specialized neural network classifier is formed by 10 beats annotated 'L' 8 beats annotated 'V', and testing set contains 40 beats 'L' and 42 beats 'V' from the specific patient 214.

The performances of the specialized classifiers was compared to the global classifiers. The results are shown in figure 4 and table 5.

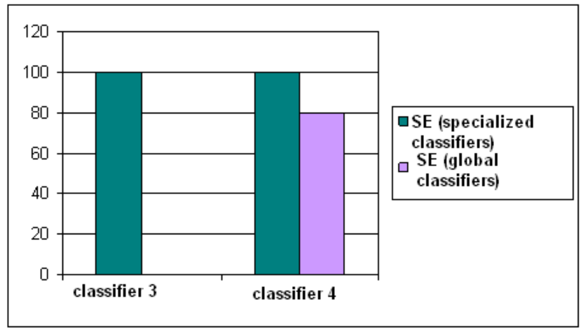

Figure 4: Comparison of sensitivity of the global and specialized classifiers.

	Specialized classifiers			Global classifiers		
	Se	Sp	CC	Se	Sp	CC
Classifier 3	100	90.476	95.122	0	98	49
Classifier 4	100	90.476	95.122	80	100	89.8990
Average	100	90.476	95.122	40	99	69.4495

Table6:Comparison of performances between the global and specialized classifiers.

We observe that the specialized classifiers performed better than the global classifiers. Moreover, we find that even with only a few beats of patient, the specialized classifiers detect LBBBs beats more accurately than global classifiers.

These remarks confirmed our claim in this paper, that patient-specific training data will significantly enhance the performance of a general neural classifier.

We notice also, that the percentage of LBBB beats, detected correctly by the specialized classifier 3 among the real number of LBBB beats presented, is improved significantly (from Se= 0% for the global classifier 3 to Se=100% after the specialized learning)

The learning and testing set are from the MIT-BIH . In most records, the upper signal is a modified limb lead II (MLII), obtained by placing the electrodes on the chest. The lower signal is usually a modified lead V1 (occasionally V2 or V5, and in one instance V4); as for the upper signal, the electrodes are also placed on the chest. In this work

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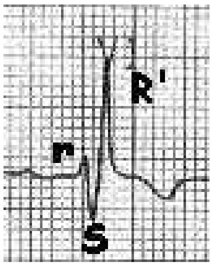
we use the upper signal in where the anomaly PVC appears but the RBBB and LBBB appears only in the precordial leads V1 and V6 as shown in figure 5 and 6(Leads V1, V2, and V3 are referred to as the right precordial leads and V4, V5, and V6 are referred to as the left precordial leads).for this reason the global classifiers obtained worst results in the recognition of RBBB and LBBB.



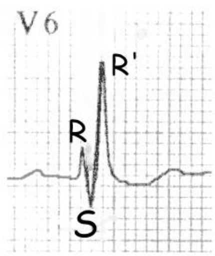


Figure 5:RBBB **Figure 6:LBBB**

4.2.2. specialized learning for classification of 'rbbb' (patient 212)

We also specialized patient 212 and the abnormality targeted in this case is the right bundle branch block 'R'.
The specialized learning set contains 5 beats 'N 'and 8 beats 'R'.

The performances of the specialized classifiers was compared to the global classifiers. The results are shown in figure 7 and table 7.

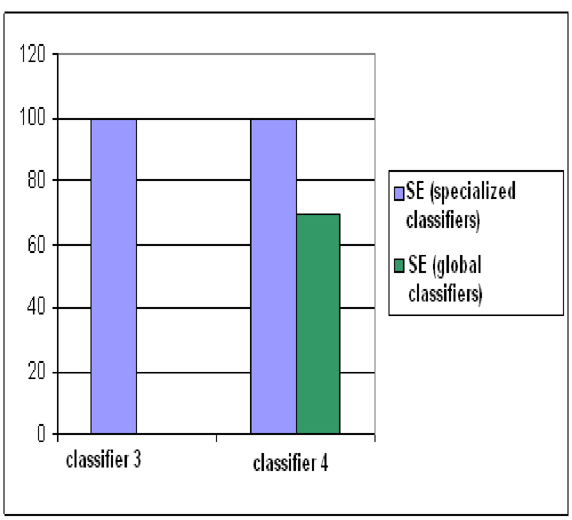


Figure 7: Comparison of sensitivity of global and specialized classifiers.

	Specialized classifiers			Global classifiers		
	Se	Sp	CC	Se	Sp	CC
Classifier3	100	100	100	0	100	16.1290
Classifier4	100	100	100	69.2308	0	58.0645
Average	100	100	100	34.6154	50	37.0975

Table 7: Comparison of performances of global and specialized classifiers.

The interest of the specialization is to permit to the classifier to improve its performances especially for recognition of cases targeted. The global classifier 3 had sensitivity equivalent to zero , after its specialization with just a few beats of cases annotated 'R' in the MIT database, the sensitivity is increased to a rate of 100% (good adaptation).

The specialized classifiers 3 and 4 recognized and correctly classified normal and pathological cases.

An ideal classifier is defined by these two characteristics ,distinguish between the cases and classify them correctly with a good generalization and avoid over fitting.
The results of specialized neural classifiers are much better than global classifiers. [21].

5.CONCLUSION

A specialized classifier to distinguish between normal ,PVC, RBBB and LBBB and in ECG signals, based on neural network architecture, is presented in this study. The effectiveness of the specialized classifier for arrhythmia classification is very promising.

In this paper, the neural network classifier is presented as diagnostic tool to aid the physician in the analysis of heart diseases.

The proposed NN classifier showed satisfactory performances in discriminating three types of

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arrhythmia. The performances of discrimination of PVC, RBBB and LBBB were respectively (sensitivity Se=93.5185% ; 100% ; 100% correct classification CC= 96.1956% ; 100% ; 95.1220%) . It is noted that the percentage of NSR segments in the dataset is high, but this is close to reality as ECG recordings have high percentages of normal beats.

The results show that the proposed method is effective for classification of cardiac arrhythmias, with an acceptable high accuracy. It is evident that the specialization of the classifier is very effective.

The main advantage of the method, compared to other approaches in the literature is that it is investigating a larger class of cardiac pathologies. our result is better than those reported in literature [3], where the best classification rate was98%.

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