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On The Analysis of a Compound Neural Network for Detecting AtrioVentricular Heart Block (AVB) in an ECG Signal

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***Abstract*—**Heart failure is the most common reason of death nowadays, but if the medical help is given directly, the patient's life may be saved in many cases. Numerous heart diseases can be detected by means of analyzing electrocardiograms (ECG). Artificial Neural Networks (ANN) are computer-based expert systems that have proved to be useful in pattern recognition tasks. ANN can be used in different phases of the decision-making process, from classification to diagnostic procedures. This work concentrates on a review followed by a novel method.

The purpose of the review is to assess the evidence of healthcare benefits involving the application of artificial neural networks to the clinical functions of diagnosis, prognosis and survival analysis, in ECG signals. The developed method is based on a compound neural network (CNN), to classify ECGs as normal or carrying an AtrioVentricular heart Block (AVB). This method uses three different feed forward multilayer neural networks. A single output unit encodes the probability of AVB occurrences. A value between 0 and 0.1 is the desired output for a normal ECG; a value between 0.1 and 1 would infer an occurrence of an AVB. The results show that this compound network has a good performance in detecting AVBs, with a sensitivity of 90.7% and a specificity of 86.05%. The accuracy value is 87.9%.

***Keywords*—**Artificial neural networks, Electrocardiogram (ECG), Feed forward multilayer neural network, Medical diagnosis, Pattern recognitionm, Signal processing.

I. INTRODUCTION

AN electrocardiogram (ECG) [1] is a noninvasive test that is used to reflect underlying heart conditions by measuring the electrical activity of the heart is obtained from electrodes placed on the surface of the body in standardized locations. An ECG is thus a plot of the time-dependence of charging potential differences between electrodes on the body surface. A typical ECG is shown in Fig.1

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The first deflection of the ECG is the P wave. Then the QRS complex is greater than the P wave. The QRS complex is as follows. Q: any initial downward deflection followed by an upward deflection. R: any upward deflection. S: any downward deflection preceded by an R wave. The T wave is considerably longer than that of the QRS complex

After inscription of the P wave, the ECG returns to its baseline. It is the interval between the P wave and the QRS complex. It represents an important index of impulse propagation through the AtrioVentricular (AV) node, AV bundle, and bundle branches. The time needed for the impulse to pass from the atria to the ventricles can be estimated from the *P-R interval*, which extends from the beginning of the P wave to the first deflection of the QRS complex.

The S-T Segment following the inscription of the QRS complex

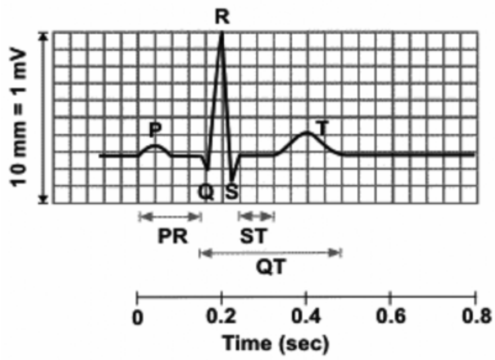

Fig. 1 The electrocardiogram (ECG).

II. SURVEY OF APPLICATIONS IN ECG

Electrocardiography has had a profound influence on the practice of medicine. The electrocardiogram contains an important amount of information that can be exploited in different manners. The ECG allows for the analysis of anatomic and physiologic aspects of the whole cardiac muscle.

They are used by hospitals to monitor patients with known or potential heart problems. By studying the electrocardiograms of the patients, cardiologists can detect rhythmic problems, heart rotation, conduction problems and some symptoms of certain diseases.

A development of the electrocardiograph was the culmination of a scientific effort aimed at perfecting a device conceived for the elucidation of a physiological phenomenon. The development of the digital computer was the culmination of scientific effort aimed at improving man's welfare. Both of these innovations of modern technology have been moderately successful in their main initial objectives.

Automatic pattern recognizers can give helps to cardiologists in detecting heart problems. It may be used in various ways in the process of medical investigations. It may serve as an independent marker for myocardial diseases, whose biomedical data may, most of the time, be represented by noisy and incomplete features with complex or even unknown relationships [2, 3]. What is required at the present time is the development of autonomous processor-based systems with sufficient processing capabilities so as to detect potential abnormalities and make accurate diagnosis in order to provide early treatments. Today, we tend to rely a great deal on the application of pattern recognition techniques to help us meet such a goal. [4].

By 1980 most of the systems, are the generation of input pattern assumes a probabilistic model. There have been several studies of automatic recognition of ECG data. Some have approached abnormality detection by studying the first difference of the waveform. Others utilize the DFT of the waveform to detect periodic components. Neither approach has produced highly accurate results [5-9].

The inclusion of artificial neural networks in the complex investigating algorithms seems to yield very interesting recognition and classification capabilities across a broad spectrum of biomedical domains. Researchers are endeavouring along this promising path. In what follows, we review some of the major achievements in the field.

By 1995 there were close on 1000 citations of neural networks in the biomedical literature [10-13], mostly describing studies with historical data, often small sets on which the predictive accuracy was tested. Most of these papers used current neural network methodologies, almost invariably the multi-layer perceptron (MLP) with 'early stopping' to prevent over-fitting.

A group of scientists are working at discriminating normal and pathological ECG complexes. The back propagation neural network is applied for that effect [14]. The network output has been able to extract the prototype complex of the analysed ECG.

Dassen *et al.* [15] described the development of a seemingly preferment neural network, designed to essentially differentiate the aetiology of wide-QRS tachycardia via a twelve-lead ECG. Nonetheless, a fundamental question remains still partially, if not entirely, unanswered. That is how to develop a reliable universal ECG interpretation system on the basis of a limited investigation process.

Conde Toni [16], for instance, suggested neural network architecture for classification, implying a Kohonen self-organising feature map and a one-layer perceptron. The recognition is feasible for five types of abnormal QRS complexes in ECG signals two of them are perfectly recognised.

Other aspects were constructed a three- layer back propagation neural network in which three features were extracted from each contour plot cycle and used as inputs to the discriminate neural network [17]. One-half of the sinus rhythm and ventricular tachycardia cycle were utilised as a training set.

On their part, ,Hoher *et al.* [18] scrutinized the capabilities of a neural network in providing reliable clinical information in order to differentiate patients with and without malignant arrhythmia on the basis of a complete QRS data processing without referring to a prior parameter extraction process.

Later, Ellenius et al [19] followed-up the diagnosis of a patient with a minor acute myocardial infarction (AMI) from the time of infarct, by monitoring the rise in the concentration of biochemical markers and identifying the stage at which the MLP, and each of three expert clinicians, could confirm the diagnosis. This unusual approach to system evaluation showed the model detecting AMI and later predicting the size of the infarct, simultaneously with the earliest firm indications by the experts.

A large-scale study of automated interpretation of 12-lead electrocardiograms for detection of AMI, was carried out with a cohort of patients presenting to a single hospital over a 5-year period, comprising 1120 confirmed cases and 10,452 controls. A 20 s trace was represented by six automatically generated ST-T measurements from each of the 12 leads, providing inputs to 72 input units of a MLP with a single hidden layer, controlled for over-training by early stopping tuned with eight-fold cross-validation [20-22].

An advanced methodological study of AMI detection in emergency departments with ANN comprises a sequence of papers by Baxt and collaborators. Early papers to optimise the accuracy of the neural network predictions [23, 24] were followed by a careful analysis of the effects of individual clinical inputs on the network decision [25], and the application of rigorous practical methodologies for sensitivity analysis [10]. Of particular interest is the use of the bootstrap to correct for finite-size effects, causing bias in the sensitivity estimates derived from the training data, a sample with 706 observations. This bias is significant enough to change the rank-order of importance of the clinical inputs.

The analysis of input effects by calculating bias corrected sensitivities in Baxt and White [13], ranked new variables higher than certain indicators commonly used by expert clinicians. The resulting model is consistent with another study of variable selection for the prediction of AMI [26] comparing multiple logistic regression (LogR), Bayesian neural networks [27] and rough sets. Several variable selection methods suited to each modelling approach were also applied to a set of 500 records, selecting from 43 variables. Multiple variable selection runs were carried out with a training data consisting of 335 patient records, optimising the results for a test set comprising the remaining 165 records. Only one variable, ST elevation, was selected by all methods.

The initial studies of a group of scientists were followed by a prospective comparison between the detection rates by cardiologists and the MLP for a cohort of 1070 patients aged 18 and over presenting with anterior chest pain, again, to a single hospital [12].

An earlier, multi-centre trial involving emergency departments in six hospitals, compared three quite different modelling structures for classification, namely rule induction, LogR and the MLP, for the prediction of acute cardiac ischemia (ACI), comprising AMI and unstable angina pectoris, from eight variables available within the first 10 min of emergency care [28]. The variables represent patient history, together with features extracted from a clinical examination and an electrocardiogram.

An altogether different application is to predict the likelihood of patients developing transient myocardial ischemia during a period with ambulatory Holler monitoring, using parameters form a previously recorded 12-lead resting ECG [29]. This is an example of a study where the MLP trained by back-propagation was out-performed by a linear discriminates analysis (LDA) and an alternative model to the MLP, the adaptive logic network.

Other different applications are to describe a key classification model and visualization platform based on self-adaptive neural networks [30], and a classification between patients and normal subjects was focus on two diseases: Obstructive Sleep Apnea (OSA) and Congestive Heart Failure (CHF) [31].

The present research work aims at developing a method based on a compound neural network composed of three different multilayer neural networks of the feed forward type. Such a network has the capability to classify ECGs as normal or carrying atrioventricular blocks (AVB).

III. Conventional Criteria of an Atrioventricular Heart Block (AVB)

An AVB [32] occurs when atrial conduction to the ventricle is for some reason blocked at a time when the AV junction is not yet physiologically refractory.

In such cases, the ECG will quite often provide adequate information to make a diagnosis regarding the presence of an AVB. As a matter of fact an AVB manifests itself, through the ECG plots, by a slowdown of the heart rate and a relative prolongation of the P-R interval to more than 0.20 s.

We can also notice either a progressive prolongation of the P-R interval prior to a non conducted P wave or a constant R-R and P-R intervals prior to a non conducted P wave Fig.2.

There are three grades of heart block.

First-Degree AV Block

The conduction through the AV node is slightly delayed but all the impulses are conducted. Thus, every P wave is followed by a QRS complex, but the PR interval is prolonged and the rhythm is regular

Type I Second-Degree AV Block

This is a partial block of the AV node. The delay at the AV node is progressively prolonged until one of the impulses is not conducted at all. The cycle then repeats. The atrial rate is unaffected, but the ventricular rate is less than atrial rate due to non conducted beats. The atrial rhythm is regular. The ventricular rhythm is irregular. The PR interval increases progressively until one QRS complex is blocked.

Type II Second-Degree AV Block

This is another form of partial AV node block. The conduction conditions are normal for most beats but some of the impulses are not conducted at all. This results in missing QRS complexes on the electrocardiogram.

The atrial rate is unaffected, but the ventricular rate is less than atrial rate due to non conducted beats. The atrial rhythm is regular. The ventricular rhythm is irregular. *Not every P wave is not followed by a QRS complex. The PR interval may be normal or prolonged but remains constant.* There may be shortening of the PR interval following the pause

Third-Degree AV Block

This is a complete AV node block and no impulses are conducted through it. In this case either AV bundle or Purkinje network became the pacemaker of the ventricles, but the atria is still paced by the sinus node. Thus, there is no correspondence between the P waves and the QRS complexes on the electrocardiogram. The atrial rate is unaffected, but the ventricular rate is slower than atrial rate. The ventricular rate is usually 40–60 beats per minute

a) A progressive prolongation of the P-R interval

b) A constant R-R and P-R intervals prior to a non-conducted P wave.

c) Two no conducted P wave

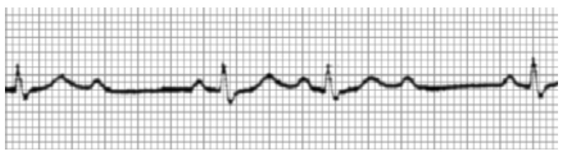

Fig. 2 Three type of AVB

IV. The Method

Our work has been organized into three parts. The first part is the population study. The second one is related to the preparation of digitized signal for input to the compound neural networks (CNN). The latter part must be realized carefully for it influences considerably the final result by minimizing the noise contained in the digitized signal and providing suitable input vectors for CNN. Finally, the third part concerns the training and recall procedures used by the CNN in the classifying process of the presented patterns .A general structure of the algorithm diagram is shown in Fig.3.

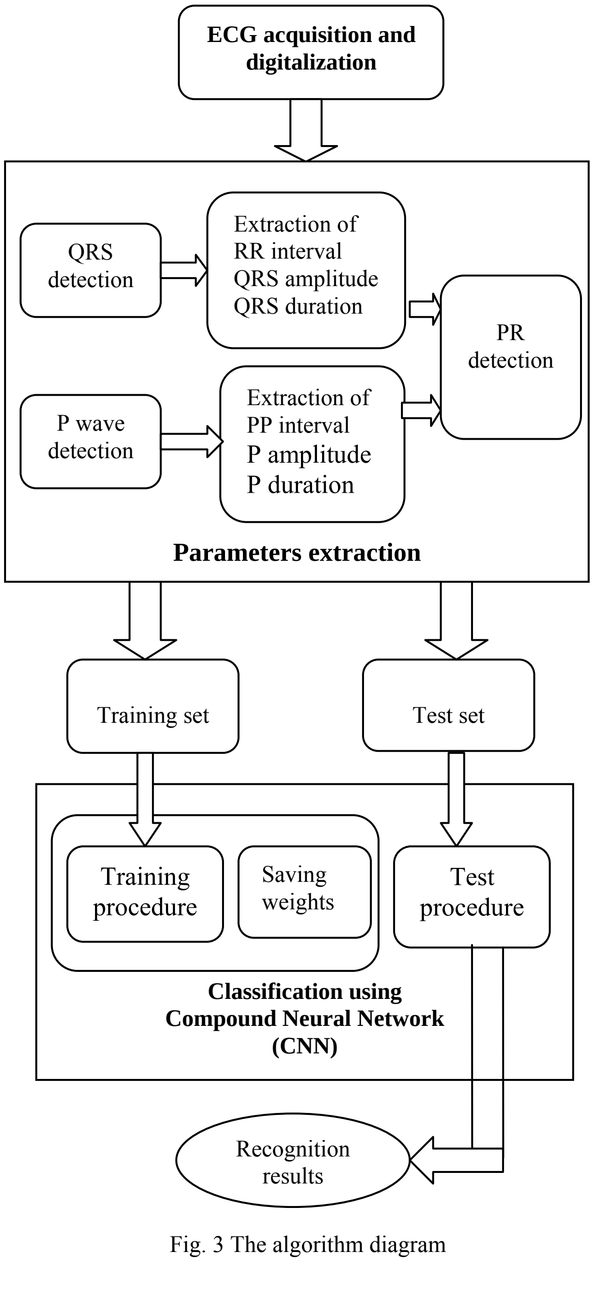

Fig. 3 The algorithm diagram

A. *Population study*

The study was based on one lead data recorded from patients who had undergone diagnostic at Constantine university hospital during the last three years. Patients are adults, both female and male, with known heart problems and symptomatic descriptions. The patients were discharged with the diagnosis AVB.

Healthy subjects were randomly selected from a defined urban population. The subjects were examined and interviewed. They had no known or suspected heart disease, or any pathological condition which may influence the ECG.

ECGs with severe technical deficiencies and pacemakers ECGs were excluded.

Several patients contributed with more than one ECG; i.e., one patient presenting to the cardiology department on two or three different occasions contributed with two or three ECGs. Each discharge diagnosis was confirmed by a cardiologist at the cardiology department.

The AVB group consists of 108 ECGs recorded on men and 90 ECGs recorded on women. The mean age was 51. The normal group consisted of 73 ECGs recorded on men and 60 ECGs recorded on women. The mean age was 48. So, there were a total of 331 ECGs.

B. *ECG analysis and parameters extraction*

The ECGs were digitalized then recorded for each individual. Samples were digitalized such that the inter signal sampling skew was on the order of a few microseconds. The analog to digital converters (ADCs) were unipolar, with 11-bit resolution over a 5 mV range. Sample values thus range from 0 to 2047 inclusive, with a value of 1024 corresponding to zero volts. We noticed that the frequency range was in accordance with the American Heart Association (AHA) specifications [33].

The definitions of the measurements follow the recommendations of the CSE working party [34]. The results are automatically obtained from one lead of the ECG (i.e. the QRS amplitudes and durations, the P amplitudes and durations, the RR intervals between two successive R waves, PP intervals between two successive P waves and PR intervals between P wave and QRS complex).These parameters were chosen because they are the conventional criteria in detecting AVB in an ECG and were applied as inputs to the CNN.

QRS detection

One of the most obvious characteristics of the QRS Complex is the large peak in R wave. A simple detection routine would just look for a periodic peak. However, because of the noise present in the acquisition of ECGs, this technique will return false waves. As a result, something more involved is required.

In first, a filter will be used to eliminate artefacts and to adjust the baseline.

In order to recognize patterns in the ECG leads, it is first necessary to locate the QRS complex. The QRS complex is a prominent waveform that appears in most normal and abnormal signals in an ECG.

The system primarily uses the neural network nodes for waveform classification. While other algorithms were considered, we decided that using a neural network would give us the best general functionality with other algorithms used secondarily for specific other characteristics.

We have used an adapter Multilayered Perceptron (MLP) for the QRS detection. A general neural network structure used in this work is shown in Fig. 4.

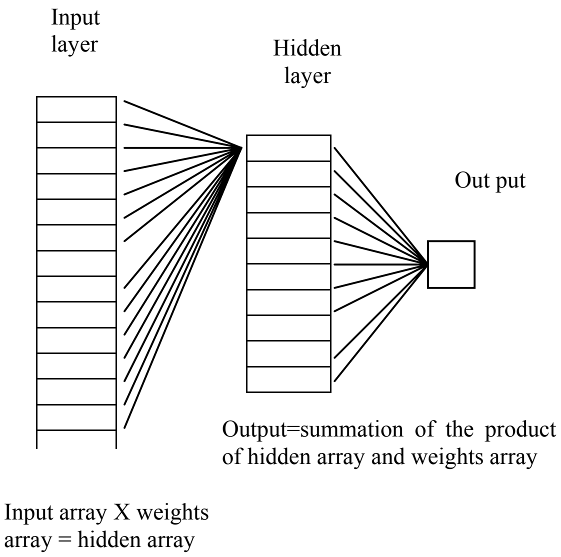

Fig. 4 The adapter Multilayered Perceptron (MLP) for the QRS detection.

MLP consists of three layers: an input layer, an output layer and a hidden layer. The processing elements or neurons in the input layer act only as input signals routing buffers to the hidden layer neurons. Each neuron in the hidden layer sums up its input signals after weighting them with the strengths of the respective connections from the input layer and computes its output by applying function on the calculated sum. The sigmoid function was chosen to compute the neurons.

For the training process the connections weights between the neurons were adjusted by using back propagation algorithm

Once the QRS is detected and located, other characteristics of the beat (QRS duration, QRS amplitude, RR interval) could be determined. A diagram of the QRS detection is shown in Fig.5

P wave detection

The P-wave is delineated after the detection of the QRS complexes. We use the same procedures as in detecting the QRS complex. So, a MLP constituted of three layers: an input layer with 14 neurones, a single output layer and hidden layer with 10 neurones. Then a set of parameters is calculated in order to specify the P wave (P duration, P amplitude and PP interval)

C. *The Compound Neural Network (CNN)*

Three different feed forward type multilayer neural networks were experimented. Two of these networks, (NN1) and (NN2), were set in a parallel configuration in series with the third one (NN3). Fig. 6 shows such a structure.

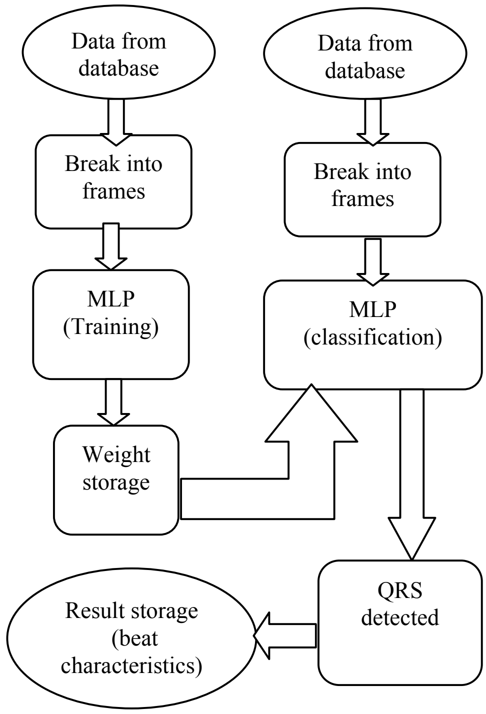

Fig. 5 Diagram of QRS detection

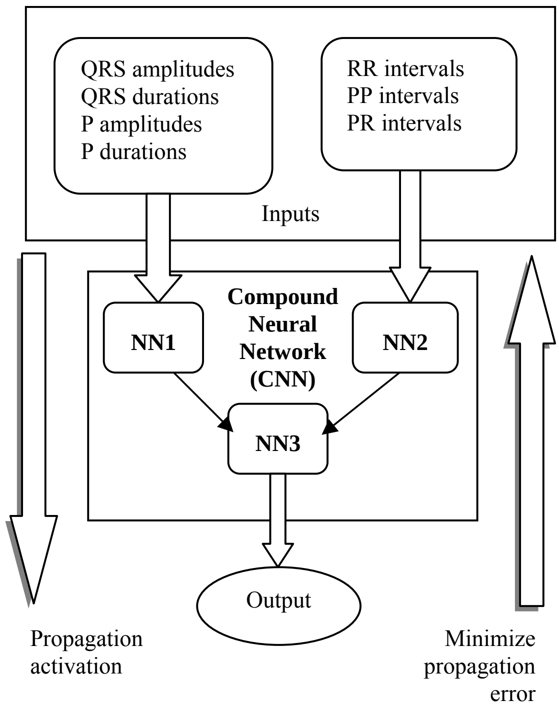

Fig. 6 The General structure of the compound neural network (CNN).

The network NN1 itself includes three layers as depicted in Fig.7. Twenty parameters are injected into the input layer. These parameters are: Five QRS amplitudes, five QRS durations, five P amplitudes and five P durations. Such a configuration calls for an input layer of at least 20 neurons.

The hidden layer has five neurons. The empirically chosen number of 5 neurons was found to avoid repetition problems and allows minimizing the training time. As for the third output layer, a single neuron was used. Its output is injected as an input to the neural network NN3.

As depicting, the three-layer neural network NN2 is constituted of fifteen neurons set to process five PR intervals, five PP intervals and five RR intervals as input parameters. The hidden layer includes three neurons while the last layer calls for a single neuron used as an input to NN3 which forms a two-layer network whose input layer is a recipient for NN1 and NN2 outputs. A terminating single output unit encodes the probability of AVB occurrences. A value within a 0 to 0.1 range implies an indication for a normal ECG while a value falling outside this range i.e. from 0.1 up to 1 suggests the presence of an AVB.

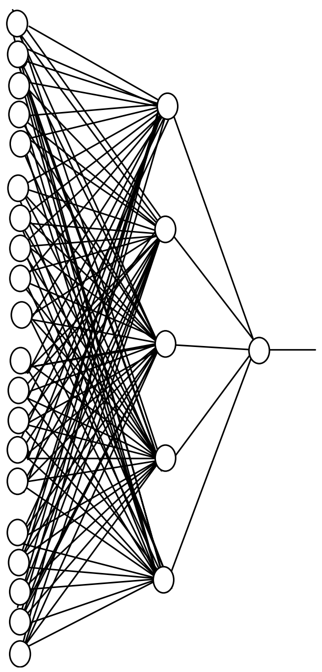

Fig. 7 Structure of the first neural network NN1

D. Study design

The acquired experimental data was subdivided into two sets: A training set and a test set. One third of the ECG data in each of the normal and AVB groups were randomly selected for the training set. The latter was used to adjust the connection weights, whereas the test set was used to assess the performance. We used a three-fold cross-validation to decide when to issue the terminate learning order to avoid "over-training" and a six-fold cross-validation to train the network and assess its performance.

Once the number of layers, and units in each layer, has been selected, the network's weights and thresholds must be set so as to minimize the prediction error made by the network. This is the role of the training algorithms. They were adjusted by using Levenberg-Marquardt algorithm. Levenberg-Marquardt is an advanced non-linear optimization algorithm. It trains the CNN in the same manner as the back propagation algorithm. Its use is restricted only on networks with a single output unit and moderate-sized feed forward neural networks (few hundred weights).It is only defined for the sum squared error function (MSE).

$$MSE = \frac{1}{N}\sum_{i}^{N} E_i^2 \tag{1}$$

E is a vector of CNN errors

$$E = output_D - output \tag{2}$$

$output_D$ is desired value and *output* is CNN output.

The algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. The Hessian matrix can be approximated as:

$$H = J^T J + \eta I \tag{3}$$

and the gradient can be computed as:

$$G = J^T E \tag{4}$$

J is the Jacobian matrix that contains first derivatives of the CNN errors with respect to the weights and biases. The Jacobian is much less complex than computing the Hessian matrix.

The algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$W_{k+1} = W_k - \left[J^T J + \eta I\right]^{-1} J^T E \tag{5}$$

W_{k+1}: value of the weight at step (k+1) after adjustment.

W_k: value of the weight at step (k) before adjustment.

The first term in the equation (5) represents the linearized assumption; the second a gradient-descent step. The control parameter governs the relative influence of these two approaches.

So, when the learning rate scalar η is zero, this is just Newton's method, using the approximate Hessian matrix. When η is large, this becomes gradient descent with a small step size.

CNN uses a sigmoid transfer function $f(x)$.

$$f(x) = \frac{1}{1 + e^{-x + bias}} \tag{6}$$

x: a vector of a layer n, defined as:

$$x = \sum_{i}^{N} a_i W_i \quad (7)$$

a_i : are the inputs.

W_i : are the weights.

This function compresses an infinite input range into a finite output range. Sigmoid functions are characterized by the fact that their slopes must approach zero as the input gets large. So the output lies between 0 and 1. It has the additional advantage of providing a form of automatic gain control.

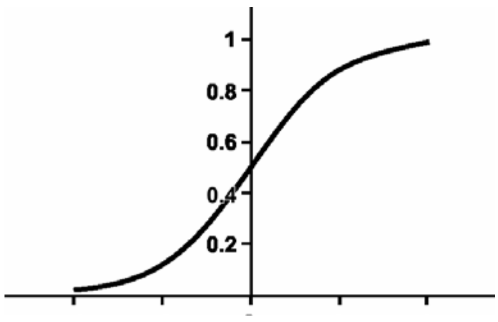

Fig. 8 The sigmoid function chosen to compute the neurons.

The learning rate (η) had a start value of 0.5. During the training η was decreased geometrically between epochs by using the following equation:

$\eta_{k+!} = l^*\eta_k$ with l=0.998 (8)

The CNN weights were initiated with random numbers between [-0.025 and 0.025]. For the two networks NN1 and NN2 a constant bias is added to all the hidden layers thereby permitting more rapid convergence of the learnig process and to avoid confusion in the classification.

The approximate memory usage for one waveform was not big it was around 24KB. The largest source of memory usage lies in the storage of the waveforms and the weights. The weights and bias are stored as 300 floats.

The size *Z* of the Jacobian matrix is:

$$Z = Q * n \quad (9)$$

Where *Q* is the number of training sets and *n* is the number of weights and biases in the CNN. *n* =166, 158 weights and 8 bias, for Q=10^5, Z= 166*10^5.

Therefore, the full Jacobian was not had to exist at one time. We computed the approximate Hessian by summing a series of subterms like update:

$$H = J^T J = \left[J_1^T J_2^T \ldots J_m^T \right] \begin{bmatrix} J_1 \\ J_2 \\ \\ J_m \end{bmatrix} = J_1^T J_1 + J_2^T J_2 \ldots + J_m^T J_m$$

Once one subterm has been computed, the corresponding submatrix of the Jacobian was cleared.

In the training we determine how many rows of the Jacobian are to be computed in each submatrix. First of all, it is set to 1, the full Jacobian is computed. It was a large training set and was running out of memory, so it should be better set to 2. The Jacobian was to be dividing into two equal submatrices. The approximate Hessian matrix was computed as follows:

$$H = J^T J = \left[J_1^T J_2^T \right] \begin{bmatrix} J_1 \\ J_2 \end{bmatrix} = J_1^T J_1 + J_2^T J_2 \quad (10)$$

The jacobian matrix *J* was not had to be computed and stored as a whole, only half of it is computed at one time. This saves half the memory used by the calculation of the full Jacobian. So memory was sufficient for storage and training.

The results show that this technique reduces the computational time and the output error. It is reputably the fastest algorithm available for such training.

Training was terminated at a training error of 10^{-25}.(Fig.9).

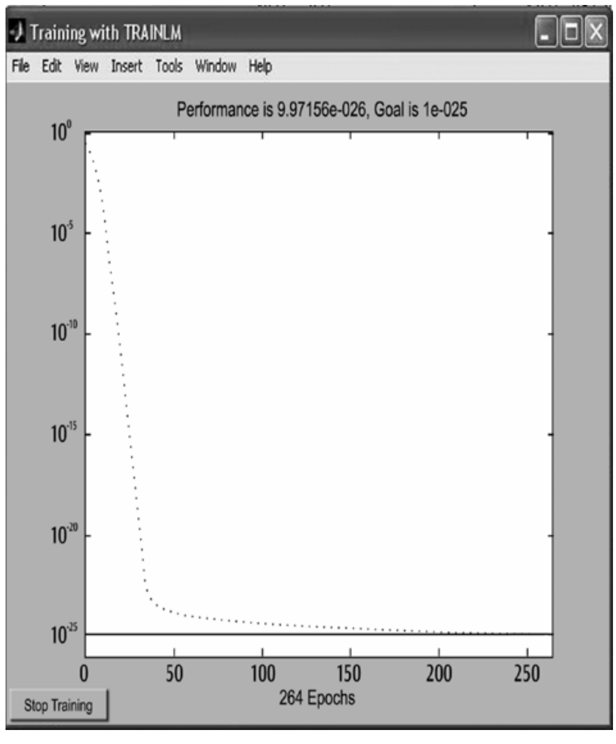

Fig. 9 training curve using Levenberg-Marquardt algorithm (broken line). The goal is terminated at a training error of 10^{-25} (solid line).

Sensitivity represents the ability of a classifier to detect the positive cases (subjects with AVB). Specificity indicates the ability of a classifier to detect negative cases, e.g. normal subjects. Accuracy represents the overall performance of a classifier. It indicates the percentage of correctly classified positive and negative cases from the total cases.

On the basis of 35% of the available data used for training purposes, and 65% for testing purposes, we found that 60% of the analysed ECGs were tagged pathological (AVB carriers). These results show that the compound network yield a high performance in detecting the presence of AVB. Its sensitivity and specificity approach 90.7% and 86.05% respectively. The accuracy value is 87.9% (see table I).

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TABLE I: STATISTIC VALUES AND RESULTS RELATING TO THE POPULATION STUDY

	ECG with AVB	Normal ECG	Total
Population	198	133	331
Training set	69	47	116
Test set	129	86	215
T_{AVB}	111	-	111
F_{AVB}	18	-	18
T_N	-	78	78
F_N	-	8	8

The table shows the detailed distribution of the experimental data using in the training set and a test set. 35% of the ECG data in each of the normal and AVB groups were selected for the training set and 65% for the test set.

V. DISCUSSION

The algorithm was found to be very fast in both test and recall states due mainly to the CNN and the fact that it calls for only one ECG lead which greatly reduces the amount of data required for processing.

The overall speed of our algorithm was very good. The generation of weights was approximately few minutes, but the verification sequence was very quick. The AVB detection looks approximately 2 seconds.

The compared previous results show that the CNN can be trained to detect AVBs from the ECG with a performance in terms of accuracy and sensitivity equivalent to what a cardiologist would achieve.

The sensitivity and specificity of the diagnostic method depend on the composition of the studied population. All recorded ECGs were included in this study except those with severe technical deficiencies or pacemaker ECGs.

All the ECGs from the group of the 18 cases falsely classified by the CNN have QRS complexes with abnormal notches. Some of them have decreasing R wave amplitude; the others have large QRS complexes.

The decreased R wave progression found in panel (b) of the Fig.14 was not a common finding the material. Therefore, this pattern might be difficult for the network.

The ECGs in Panels (c and d) have large QRS complexes. This is not a normal finding and the CNN classification is therefore not surprising. This information is not given to the network; the training used only normal QRS. To resolve this problem, it could be to add an expert to the CNN.

Fig. 10 shows the final results of ten examples, randomly chosen, given by the CNN.

Seven out put values of the CNN from the group incorrectly classified are presented in table III and Fig.13.

These good results confirm that neural networks can be reliably used to improve automated ECG interpretation process for AVB and that even an experienced cardiologist could use such networks as an essential decision-making support. This improvement will lead, in the near future, to a more accurate early diagnosis of AVB.

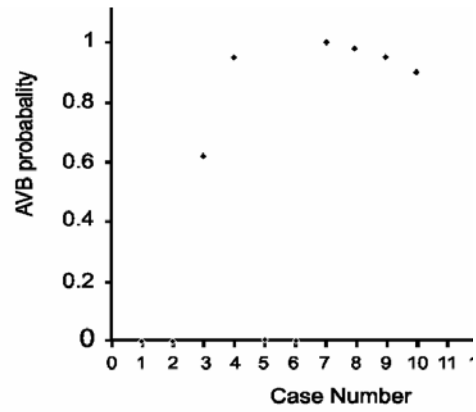


Fig. 10 Diagram of output values of the CNN using the measurements from the ten data sets. When the outputs above a threshold of 0.1 were classified correctly.

TABLE II: RESULTS RELATING TO TEN ECGS RANDEMLY CHOSEN FROM THE TEST A SET

ECG	CNN OUTPUT	Cardiologist
ECG_1	0.0000	Normal
ECG_2	0.0006	Normal
ECG_3	0.6200	AVB
ECG_4	0.9505	AVB
ECG_5	0.0080	Normal
ECG_6	0.0010	Normal
ECG_7	1.0000	AVB
ECG_8	0.9800	AVB
ECG_9	0.9500	AVB
ECG_{10}	0.9000	AVB

Fig. 11 Fore Normal ECGs randomly chosen from the test set ECGs, correctly classified by the compound neural network (CNN)

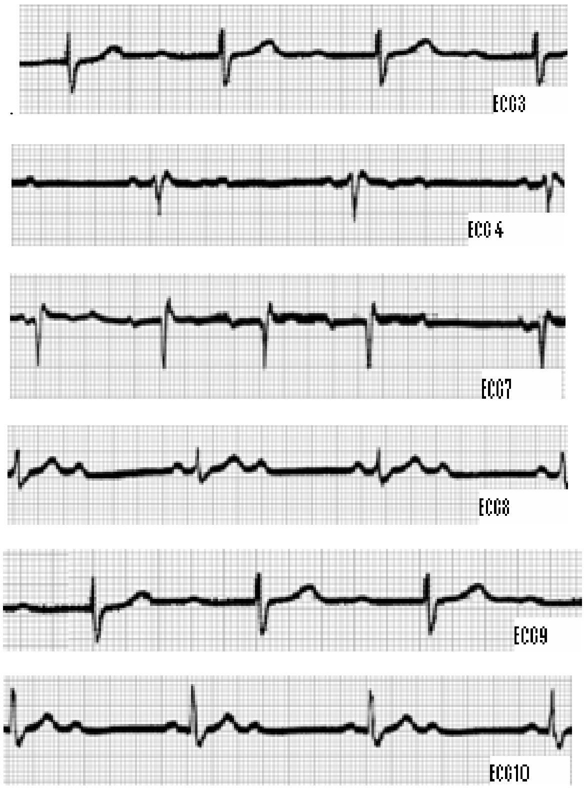
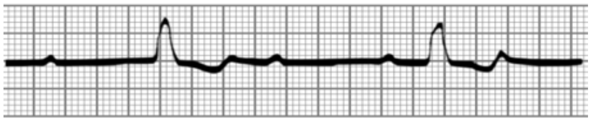
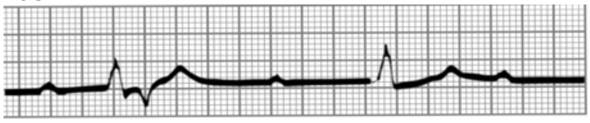


Fig. 12 Six ECGs carrying AVB randomly chosen from the test set ECGs correctly classified by the compound neural network (CNN).

ECG 11

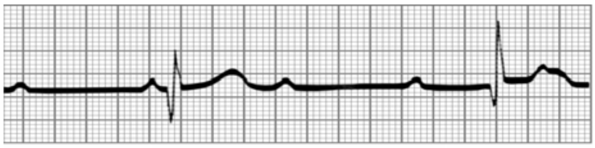


ECG 12



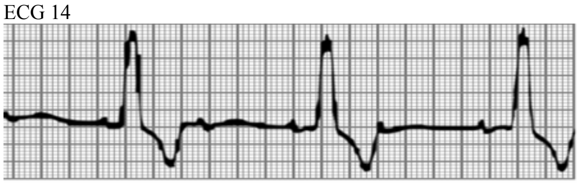
a) ECGs have QRS complexes with abnormal notches.

ECG 13



b) ECG with decreased R wave

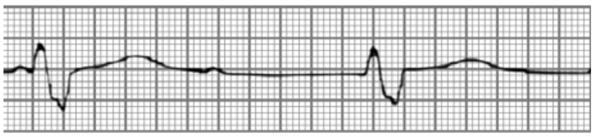
ECG 14



ECG 15

c) ECGs with large QRS

ECG 16



ECG17

d) ECGs with very large QRS

Fig. 14 The ECG from the test set incorrectly classified by the CNN.

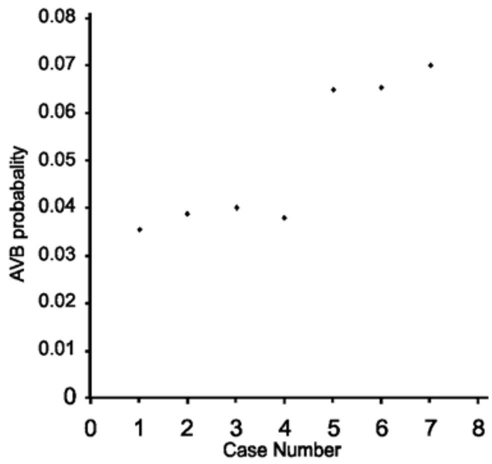


Fig. 13 Diagram of output values of the CNN using the measurements from the seven data incorrectly classified

TABLE III: RESULTS RELATING TO TEN ECGS CHOSEN FROM THE GROUP INCORECTLY CLASSIFIED

ECG	CNN OUTPUT	CARDIOLOGIST
ECG_{11}	0.0353.	BAV
ECG_{12}	0.0386	BAV
ECG_{13}	0.0400	BAV
ECG_{14}	0.0389	BAV
ECG_{15}	0.0650	BAV
ECG_{16}	0.0653	BAV
ECG_{17}	0.0700	BAV

VI. CONCLUSION

We have presented a method for automated detection of AVB patients using one lead ECG. The lead was digitalized and the measurements were used as inputs to the CNN classifier that were trained to detect AVB. The performance was compared with that of an experienced cardiologist. No significant difference was found. The sensitivity and specificity were 90.7% and 86.05% respectively.

With proper further developments, we believe the proposed method has potential as a decision support system that can provide a good suggestion for diagnosis, as well as providing the physician with insight into the reason underlying the advice.

The CNN used in the present work can be incorporated in computer-based ECG interpretation system in order to detect AVB in ECG waveforms. Such implementations would yield higher performance particularly in cardiology departments.

Schwartz [35] predicted that by the year 2000 computers would 'have an entirely new role in medicine, acting as a powerful extension of the physician's intellect'. This prediction is being true of developments in medical instrumentation, physiology signals and radiology involved first generation neural networks.

Neural networks have a niche to carve in clinical decision support, in order to produce the simplest and most transparent overall reasoning structure, and they will to evaluate this in a real clinical environment.

In the future, the role of computers in medicine will be substantially extended along several directions. These range from patient management, with the development of application service providers and knowledge-based decision support systems, through increased sophistication in electronic systems for data acquisition, storage and transmission, spurred-on by a gradual acceptance of industry standards such as extensible mark-up languages, onto the emergence of radically new applications in telemedicine and self-care.

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