Agreement Between Multi-Layer Perceptron and a Compound Neural Network on ECG Diagnosis of Aatrioventricular Blocks

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Abstract: - 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. In this work, we develop two methods. The first one based on a compound neural network (CNN) composed of three different multilayer neural networks of the feed forward type, and the second one based on only a multi-layer perceptron (MLP). Such both of them have the capability to classify electrocardiograms (ECG) as normal or as carrying atrioventricular blocks (AVB). These networks were fed with same measurements from one lead of the ECG. A single output unit encodes the probability of AVB occurrences. The difference in performance between the two neural networks classifiers was measured as the difference in area under the receiver operating characteristic curves (ROC). The results show that the CNN and MLP have a good performance in detecting AVBs.

Key-Words: - Artificial neural networks, Biomedical data, Electrocardiogram (ECG), Medical diagnosis, Pattern recognition, Signal processing,

1 Introduction

Electrocardiograms (ECG) are used by hospitals to monitor patients with known or potential heart problems. The ECG is composed of 12 leads. One lead may include P wave, QRS complex and T wave. By studying the electrocardiograms of the patients, cardiologists can detect rhythmic problems, heart rotation, conduction problems and some symptoms of certain diseases [1].

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. 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 [2-4]. Today, we tend to rely a great deal on the application of pattern recognition techniques to help us meet such a goal. There have been several studies of automatic recognition of ECG data [5-8].

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 [9]. In the two last decades, there were close on 1000 citations of neural networks in the biomedical literature [10], 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 [11]. The network output has been able to extract the prototype complex of the analysed ECG.

Dassen et al. [12] 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 [13], 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 [14]. One-half of the sinus rhythm and ventricular tachycardia cycle were utilised as a training set.

On their part, ,Hoher et al. [15] 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 [16] 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 [17-19].

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 [20, 21] were followed by a careful analysis of the effects of individual clinical inputs on the network decision [22], and the application of rigorous practical methodologies for sensitivity analysis [23]. 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 [24], 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 [25] comparing multiple logistic regression (LogR), Bayesian neural networks [26] 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 [27].

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, 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 and an alternative model to the MLP, the adaptive logic network.

In [30] the others have used Bayesian ANNs as a tool for detecting AMI patients using the 12-lead ECG. Furthermore, to explain the reasoning behind the ANN output, a method was developed that aims at showing regions of the ECG important for this particular case. The key ingredients of their approach are: a representation of the ECG using Hermite functions, and a combinatorial optimization problem formulation for finding important ANN inputs.

Other different applications are to describe a key classification model and visualization platform based on self-adaptative neural networks [31], a classification between patients and normal subjects was focus on two diseases: Obstructive Sleep Apnea (OSA) and Congestive Heart Failure (CHF) [32].

The present research work aims at developing two approaches. The first one based on a compound neural network (CNN) composed of three different multilayer neural networks of the feed forward type, and the second one based on only a multi-layer perceptron (MLP). Such both of them have the capability to classify ECGs as carrying atrioventricular blocks (AVB) or not.

An AVB 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 [33].

2 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 two neural networks; CNN and MLP. 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 Neural Networks. The third part concerns the training and recall procedures used by the Two networks whose were trained to classify ECGs AVB or no AVB (i.e. or normal) these networks were fed with same measurements from lead II but in different architectures. Finally, performance assessment of the two approaches in detecting AVB was presented in receiver operating characteristic curves (ROC). .A general structure of the algorithm diagram is shown in Fig.1.

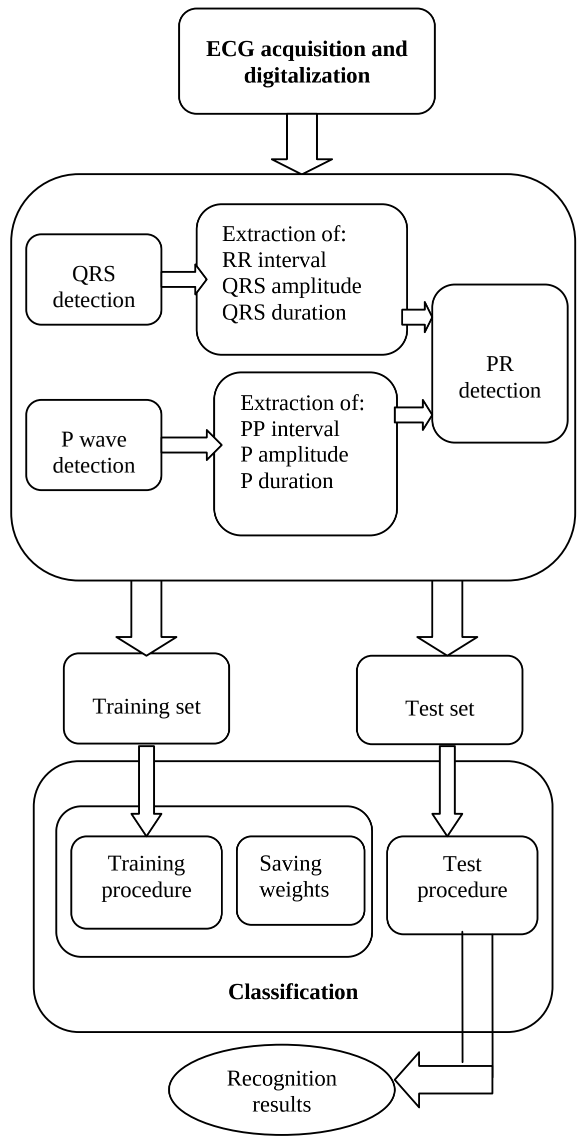


Fig. 1 The algorithm diagram

2.1 Population Study

The study was based on one lead data recorded from patients who had undergone diagnostic at the hospital during the last four 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 normal group consisted of 73 ECGs recorded on men and 60 ECGs recorded on women. So, there were a total of 331 ECGs.

2.2 Recording Technique

All recordings were made digitally. We noticed that the frequency range of the Samples was in accordance with the American Heart Association (AHA) specifications [34]. And the measurements follow the recommendations of the CSE working party [35]. Measurements durations and amplitudes of the waves and the intervals were performed using custom software. In first, a filter will be used to eliminate artefacts and to adjust the baseline in order to recognize patterns in the ECG leads.

The system 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. The following automated measurements from the lead II were considered in the present study: 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 and MLP. These measurements were obtained from the computerized ECG recorders using their measurements program.

2.3 Multi-Layer Perceptron (MLP) Architecture

A feed forward type multilayer neural network was experimented. The network itself includes three layers as depicted in Figure.2.

The thirty five parameters are injected into the input layer. These parameters are: Five QRS amplitudes, five QRS durations, five P amplitudes, five P durations, five PR intervals, five RR intervals and five PP intervals durations. Such a configuration calls for an input layer of at least 35 neurons.

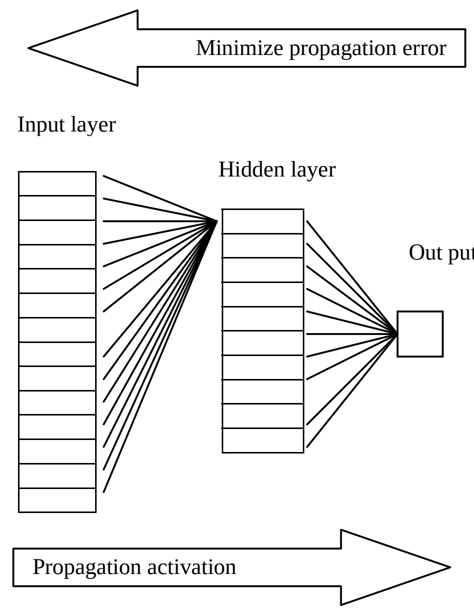


Fig.2. The adapter Multilayered Perceptron (MLP) for the AVB detection.

The hidden layer has ten neurons. The empirically chosen number of 10 neurons was found to avoid repetition problems and allows minimizing the training time. Each of the neurons in the hidden layer was connected to all of the neurons in the input layer and to the neuron in the output layer. Each connection was characterized by separate weight. The weights were used in the calculations producing numerical output as results of electrocardiographic measurements fed to the network. In a learning process the weights were automatically adjusted using the levenberg-Markwed algorithm in order to give the desired output of each of the ECGs in the learning set. After the learning process was completed, the weights were fixed and all ECGs in the test set were processed once by the network. The terminating single output unit encodes the probability of AVB occurrences.

2.3 Compound Neural Network (CNN) Architecture

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. 3 shows such a structure.

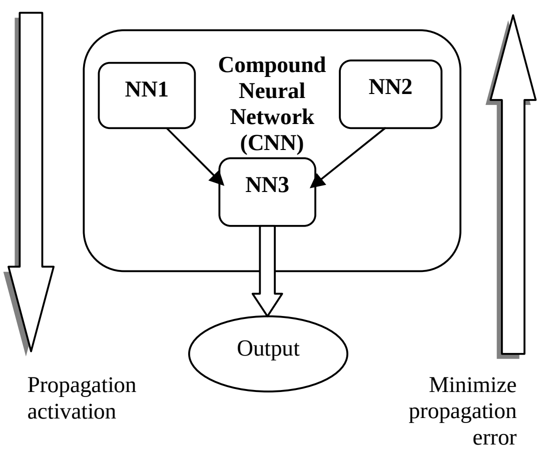


Fig.3 The General structure of the compound neural network (CNN).

The network NN1 itself includes three layers. Twenty parameters are injected into the input layer. These parameters are: Five QRS amplitudes, five QRS durations, five P amplitudes and five P durations. The hidden layer has five neurons. As for the third output layer, a single neuron was used. Its output is injected as an input to the neural network NN3.

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.

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

2 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 learning terminate order to avoid “over-training” and a six-fold cross-validation to train the networks and assess their performance.

Te weights of the two neural networks were adjusted by using Levenberg-Marquardt algorithm. Levenberg-Marquardt is an advanced non-linear optimization algorithm. It trains the CNN and LMP 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 reputably the fastest algorithm available for such training.

MLP and CNN use a sigmoid transfer function $f(x)$.

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

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

$$x = \sum_{i}^{N} a_i W_i \tag{2}$$

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

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

$$W_{k+1} = W_k - \left[J^T J + \eta I\right]^{-1} J^T E \quad (3)$$

J: the Jacobian matrix is much less complex than computing the Hessian matrix.

Wk+1: value of the weight at step (k+1) after adjustment and Wk: value of the weight at step (k) before adjustment.

The first term in the equation (3) 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.

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:

$$\eta_{k+1} = l * \eta_k \quad (4)$$

with

$$l = 0.998$$

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

In the MPL network, a constant bias is added to all the neurons of the hidden layer 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:

$$Z = Q * n \quad (5)$$

Where Q is the number of training sets and n is the number of weights and biases in the two neural networks.

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:

$$H = \left[J_1^T J_2^T\right] \begin{bmatrix} J_1 \\ J_2 \end{bmatrix} = J_1^T J_1 + J_2^T J_2 \quad (7)$$

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.

For training CNN only half of it was computed at one time. However, in MLP training the jacobian matrix J was not had to be computed and stored as a whole, it was a large training set and was running out of memory, so it should be better set to 4. The Jacobian was divided into four equal submatrices as follows:

$$H = \left[J_1^T J_2^T J_3^T J_4^T\right] \begin{bmatrix} J_1 \\ J_2 \\ J_3 \\ J_4 \end{bmatrix} = J_1^T J_1 + J_2^T J_2 + J_3^T J_3 + J_4^T J_4$$

The results show that these techniques reduce the computational time and the output errors. Training was terminated at a training error of 10^{-25} after 264 iterations for CNN (Fig.5) and 10^{-25} after 532 iterations for MLP (Fig.6). Each network had one output neuron. The out put of the networks was a number between 0 and 1. The desired output of a network classifying ECGs as AVB or no AVB was 1 for AVB and 0 for no AVB.

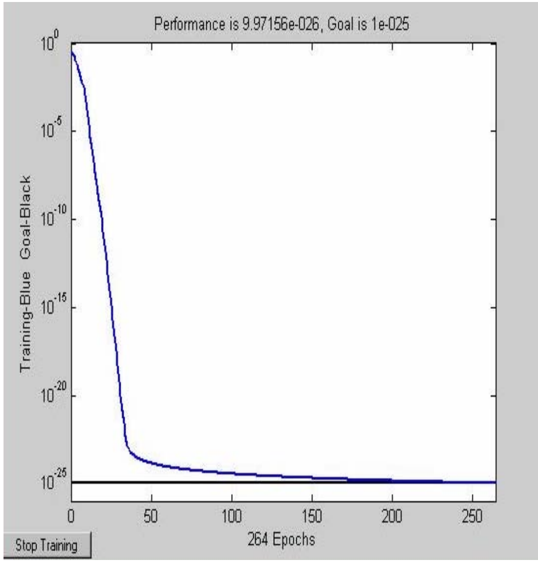


Fig.5 The CNN training curve using Levenberg-Marquardt algorithm. The goal is terminated at a training error of 10^{-25} after 264 iterations.

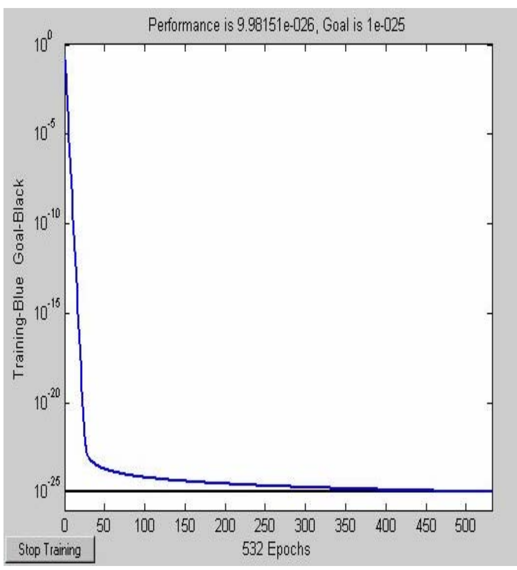


Fig.6 The LMP training curve using Levenberg-Marquardt algorithm. The goal is terminated at a training error of 10^{-25} after 532 iterations.

4 Performance Assessments of the CNN and MLP

The performance of the neural networks classifiers was assessed using the test set comprising 215 randomly selected patients from the total population of 331 cases (table 1). This test set was not part in any algorithm design or model selection. For each test case in the test set the neural networks classifier present an output value between 0 and 1. A threshold in this interval was used above which all values were regarded as consistent with AVB.

	ECG with AVB	Normal ECG	Total
Population	198	133	331
Training set	69	47	116
Test set	129	86	215

Table 1: Statistic values relating to the population study for the MLP architecture and CNN architecture

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.

To evaluate the performance of the classifiers three statistical formulas are used: specificity, sensitivity and accuracy as defined in equations 9, 10 and 11.

$$specificity = \frac{T_n}{T_n + F_{AVB}} 100 \quad (9)$$

$$sensitivity = \frac{T_{AVB}}{T_{AVB} + F_n} 100 \quad (10)$$

$$accuracy = \frac{T_{AVB} + T_n}{T_{AVB} + F_n + T_n + F_{AVB}} 100 \quad (11)$$

Where:

T_n (True normal) is the number of normal ECG recognized as normal.

T_{AVB} (True AVB) is the number of ECG carrying AVB recognized as AVB.

F_n (False normal) is the number of ECG carried AVB recognized as normal.

F_{AVB} (False AVB) is the number of normal ECG recognized as AVB.

The sensitivity and specificity for different thresholds were studied in order to obtain a complete receiver-operating characteristic curve (ROC) for the networks. The results subsequently presented the performances of the networks in the set.

The difference in performance between the two neural networks classifiers was measured as the difference in area under the ROC curves. The statistical significance of such an observed area difference was assessed by means of a permutation test as follows.

A new classification list was created by randomly selecting for each of the 215 test cases either the classification made with the CNN or the classification made with the MLP. A second list was created from the classification not included in the first one. The two lists were used to construct two ROC curves, and the areas under the curves were calculated, as was the area difference (test statistic). The procedure was repeated many times. The relative frequency of area differences that had an absolute value greater than the actual difference was taken as the probability of obtaining at least the actual area difference if no true difference existed.

5 Results and discussion

The objective of the present study was to compare the performance of two different neural networks; the CNN and MLP architectures.

The CNN algorithm was found to be very fast in both test and recall states due mainly to its architecture 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 the 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 MLP was not as fast as CNN, the training time was more then 10 minutes and the test time was approximately 10 seconds.

The CNN shows a higher sensitivity for all specificities in the range 90% to 100%. However, the difference in sensitivity between the two networks, at a specificity of 99%, was 42% of MLP and 47% vs. 79% of CNN and this difference was highly significant. The significance of the difference in sensitivity between the CNN and MLP was tested with intention to the fact that the same ECGs were used.

Together with the corresponding output values of the CNN, a threshold of 0.1 was used to give sensitivity and specificity 92.31% and 98.39%, respectively. For the MLP the sensitivity was 83% and the specificity was 93.38%. The ECGs with output values close to 1 lack clear electrocardiographic signs of AVB and those with output values close to 0 are clear normal (Fig.7).

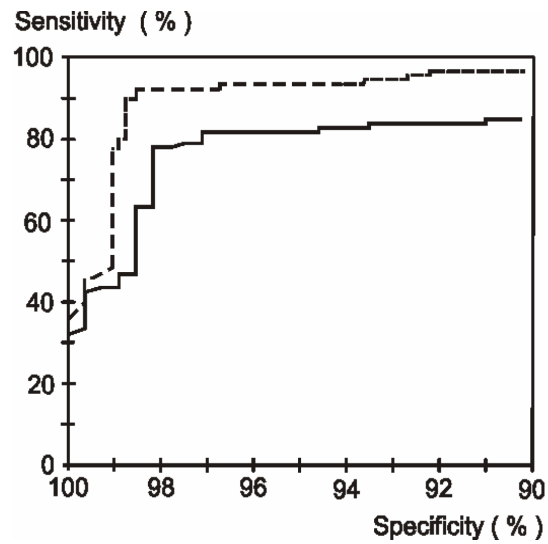


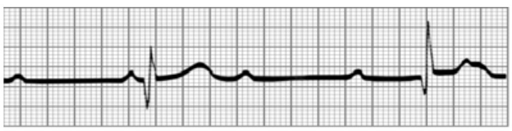
Fig. 7 Receiver operating characteristic curve for the networks diagnosing AVB in the test set. One MLP network (solid line) and the other one CNN network (broken line).

	ECG with AVB	Normal ECG	ECG with AVB	Normal ECG
	CNN	architecture	**MLP**	architecture
T_{AVB}	122		113	
F_{AVB}	7		16	
T_N		84		78
F_N		2		8

Table 2: Results relating to the population study for the MLP architecture and CNN architecture using a threshold of 0.1.

In the classification of the ECGs by the CNN and the MPL, there was agreement in 191 ECGs. The 6 ECGs on which the CNN and MLP disagreed, and on which the network was incorrect constitute a particularly interesting group one of the six ECGs had serious errors in the data of the measurement program and was therefore not properly presented to the networks

a) ECGs have QRS complexes with abnormal notches.



b) ECG with decreased R wave

c) ECGs with large QRS

d) ECGs with very large QRS

Fig.8 ECGs from the test set incorrectly classified by the CNN.

All the ECGs from the group of the 7 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.8 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.

4 Conclusion

We have presented two methods for automated detection of AVB patients using one lead ECG. The lead was digitalized and the measurements were used as inputs to the CNN and MLP classifiers that were trained to detect AVB and the same ECGs were used in the test. The performance was compared with that of an experienced cardiologist to whom we presented all the ECGs in random manner. The cardiologist classified each of the ECGs; the results were available at the classification procedure from the CNN. No significant difference was found. The sensitivity and specificity were 92.30% and 98.39% respectively. For the MLP the sensitivity was 83% and the specificity was 93.38%.

The compared previous results show that the CNN and MLP, both of them 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

With proper further developments, we believe the proposed CNN has potential as a decision support system that can provide a good suggestion for diagnosis.

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.

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.

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