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A High Performance CNN Architecture for the Detection of AVB Carrying ECGs

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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 research, we develop a method, 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 the CNN has a good performance in detecting AVBs, with a sensitivity of 89% and a specificity of 86%.

Key words: Artificial neural networks, biomedical data, Electrocardiogram (ECG), pattern recognition, signal processing

INTRODUCTION

Normally an Electrocardiogram (ECG) is composed of 12 leads of data generated by attaching 12 separate electrodes to the patient. The elements of an ECG may include a preliminary P wave, a Q peak (negative amplitude), an R peak (the most prominent feature), an S peak (negative amplitude) and a T wave, as shown in Fig. 1.

Electrocardiograms 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.

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 (Baldi and Brunak, 2000; Hudson and Cohen, 2000). 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. (Liebman, 2002). There have been several studies of automatic recognition of ECG data.

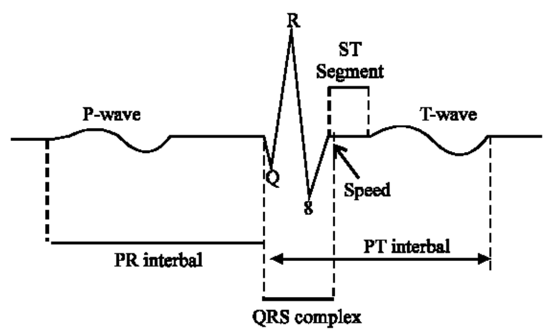

Fig. 1: The Electrocardiogram (ECG)

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.

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 (Meghriche and Boulemden, 2007).

Conde (1994) 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.

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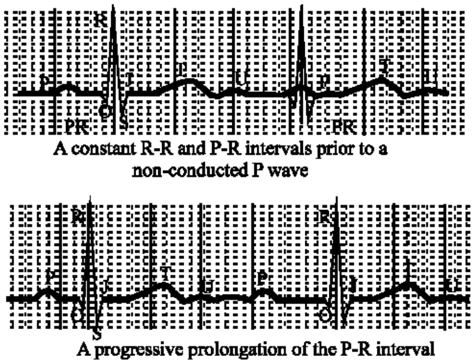


Fig. 2: Two type of AVB

Other scientists are working at discriminating normal and pathological QRS complexes. The back propagation neural network is applied for that effect (Casaleggio *et al*., 1991; Dassen *et al*., 1992).

Heden *et al.* (1993, 1994, 1997) put forward the results of a scientific research work in which they explored the sensitivity/specificity relationships for neural networks in the diagnosis of healed myocardial infarction. When compared with what conventional interpretation systems yield, their results were judged more reliable regarding the diagnosis of myocardial infarction.

Other aspects were studied and systems were developed, on their part, scrutinized the capabilities of a neural network in providing reliable clinical information in order to differentiate patients with and without malignant arrhythmia (Hoher *et al*., 1995) or to differentiate the sinus rhythm and ventricular (Ming-Chuan *et al*., 1994).

A supervised neural network based algorithm was used to detect ischemic episodes from ECG (Malgaveras *et al*., 1992, 1994).

Haiying *et al.* (2004) described a key classification model and visualization platform based on self-adaptative neural networks.

A classification between patients and normal subjects was focus on two diseases: Obstructive Sleep Apnea (OSA) and Congestive Heart Failure (CHF) (Abdulnasir, 2006).

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).

Conventional criteria of An atrioventricular heart block (AVB): 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 (Fig. 2).

MATERIALS AND METHODS

Our research 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.

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.

ECG analysis parameters extraction: The ECGs were digitalized then recorded for each individual. Samples were digitalized such that the inter signal sampling skew

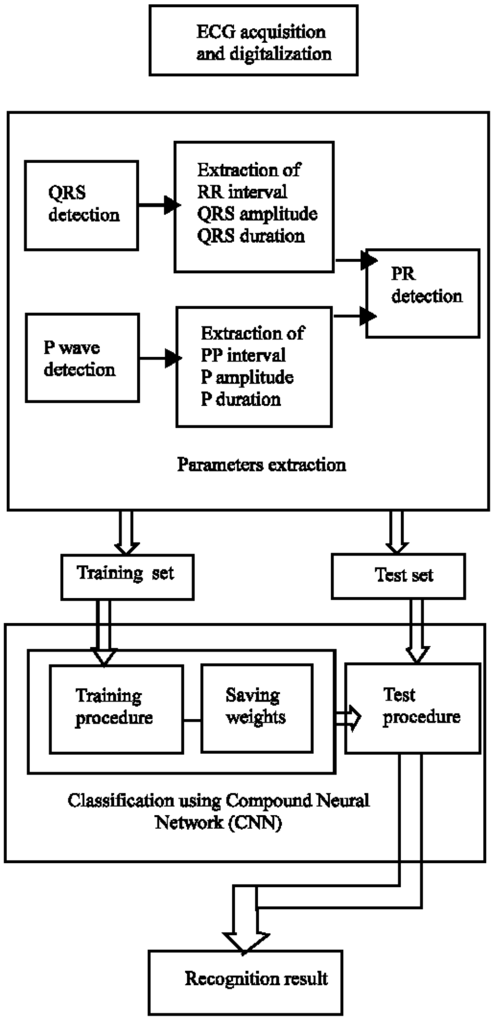


Fig. 3: The algorithm diagram

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 (New York Heart Association, 1953).

The definitions of the measurements follow the recommendations of the CSE working party (Rantahaju *et al*., 1978). 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.

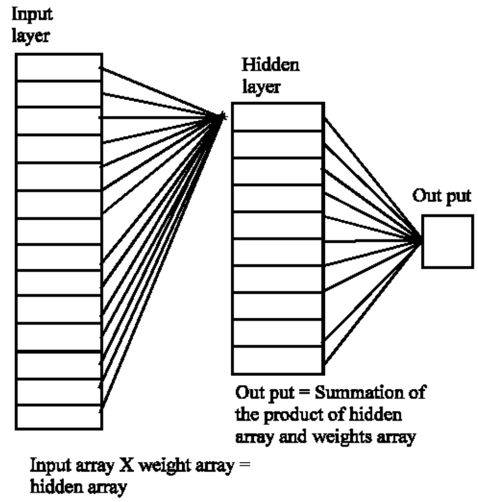


Fig. 4: The adapter Multilayered Perceptron (MLP) for the QRS detection

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 research is shown in Fig. 4. MLP consists of three layers: An input layer, an output layer and hidden layer. The processing elements or neurons in the input layer only act as buffers for distributing the input signals to neurons in the hidden layer. 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

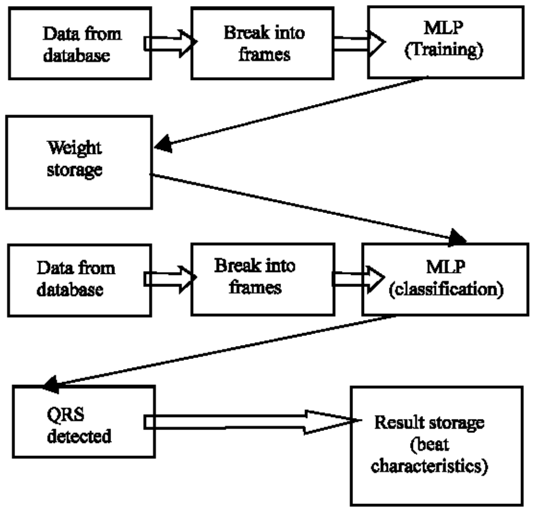


Fig. 5: Diagram of QRS detection

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 (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).

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). Figure 6 shows such a structure.

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. 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.

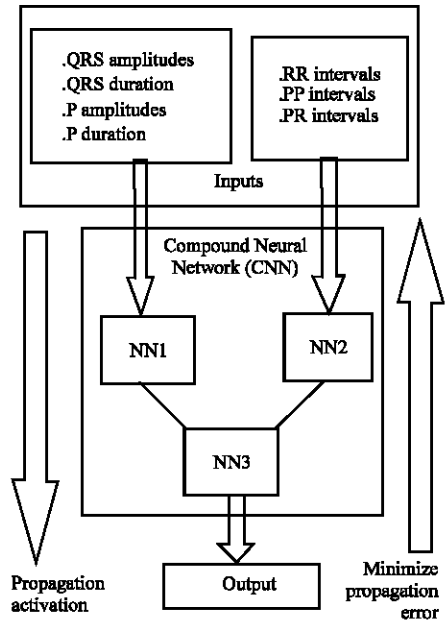


Fig. 6: The General structure of the Compound Neural Network (CNN)

The three-layer neural network NN2 is constituted of 15 neurons set to process 5 PR intervals, 5 PP intervals and 5 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.

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

To that effect, a sigmoid transfer function was used. Training was terminated at a training error of 10^{-25}. The network weights were initiated with random numbers. For the two networks NN1 and NN2 a constant bias is added to all the hidden layers to avoid confusion in the classification.

The performance of the compound neural network was compared with that of an experienced cardiologist to whom we presented all the ECGs in a random manner. The cardiologist classified each of the ECGs; the results were available at the classification procedure from the CNN.

The performance of a classifier is evaluated by three statistical formulas: specificity, sensitivity and accuracy as defined in Eq. 1-3.

$$\text{Specificity} = \frac{T_n}{T_n + F_{AVB}} 100 \tag{1}$$

$$\text{Sensitivity} = \frac{T_{AVB}}{T_{AVB} + F_n} 100 \tag{2}$$

$$\text{Accuracy} = \frac{T_{AVB} + T_n}{T_{AVB} + F_n + T_n + F_{AVB}} 100 \tag{3}$$

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.

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. Figure 7 and Table 1 show the final results of 10 examples given by the CNN.

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, this compound network yield a high performance in detecting the presence of AVB. Its sensitivity and specificity approach 89 and 86%, respectively. The accuracy value is 88%.

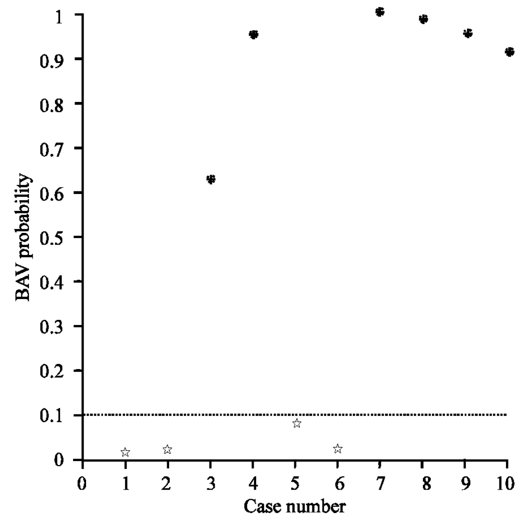
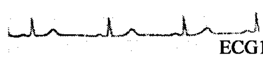
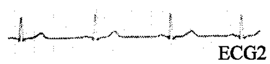
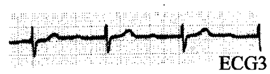
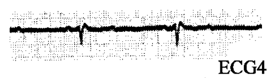
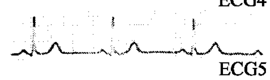
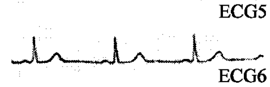
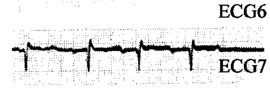
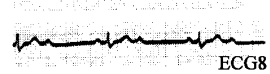
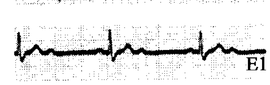


Fig. 7: Diagram of output values of the CNN that used the measurements from the 10 examples. When the outputs above a threshold of 0.1 were classified correctly

Table 1: Results relating to 10 ECGs

ECGs	CNN output	Cardiologist
 ECG1	0.0000	Normal
 ECG2	0.0006	Normal
 ECG3	0.6200	AVB
 ECG4	0.9505	AVB
 ECG5	0.0080	Normal
 ECG6	0.0010	Normal
 ECG7	1.0000	AVB
 ECG8	0.9800	AVB
	0.9500	AVB
 E1	0.9000	AVB

CONCLUSION

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 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.

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.

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.

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