Neural networks – a diagnostic tool in acute myocardial infarction with concomitant left bundle branch block

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Summary

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The prognosis of acute myocardial infarction (AMI) improves by early revascularization. However the presence of left bundle branch block (LBBB) in the electrocardiogram (ECG) increases the difficulty in recognizing an AMI and different ECG criteria for the diagnosis of AMI have proved to be of limited value. The purpose of this study was to detect AMI in ECGs with LBBB using artificial neural networks and to compare the performance of the networks to that of six sets of conventional ECG criteria and two experienced cardiologists. A total of 518 ECGs, recorded at an emergency department, with a QRS duration >120 ms and an LBBB configuration, were selected from the clinical ECG database. Of this sample 120 ECGs were recorded on patients with AMI, the remaining 398 ECGs being used as a control group. Artificial neural networks of feed-forward type were trained to classify the ECGs as AMI or not AMI. The neural network showed higher sensitivities than both the cardiologists and the criteria when compared at the same levels of specificity. The sensitivity of the neural network was 12% (P = 0·02) and 19% (P = 0·001) higher than that of the cardiologists. Artificial neural networks can be trained to detect AMI in ECGs with concomitant LBBB more effectively than conventional ECG criteria or experienced cardiologists.

Introduction

It has been demonstrated that the prognosis of acute myocardial infarction (AMI) improves by early revascularization (Kleiman et al., 1994) (Muller & Topol, 1990); thus early diagnosis of AMI is of vital importance. However, as the 12-lead electrocardiogram (ECG) is still the best and most readily available device for such investigation and as the presence of left bundle branch block (LBBB) makes the electrocardiographic manifestations of acute myocardial ischaemia difficult to detect, the presence of LBBB is an issue of major diagnostic importance. In unselected populations of patients with myocardial infarction the prevalence of LBBB has been shown to be 5–10% (Eriksson et al., 1998).

According to the recommendation of the ACC/AHA (ACC/AHA Guidelines, 1999), patients presenting with symptoms suggestive of AMI and concomitant LBBB should be considered for reperfusion therapy. Using this approach there is a risk that patients without AMI are treated with thrombolysis thus inducing a risk of bleeding and other adverse effects. The opposite approach, not to treat patients with LBBB, would exclude those patients with AMI from the benefits of reperfusion. It is therefore of interest to develop more accurate methods for the early diagnosis of AMI in patients with LBBB.

Artificial neural networks have already been applied to different aspects of automated interpretation of ECGs, for example in the diagnosis of healed myocardial infarction (Heden et al., 1994; Heden et al., 1996) and AMI (Heden et al., 1997). These studies using neural networks have demonstrated a significantly improved performance over both conventional ECG criteria and experienced ECG readers.

The purpose of this study was to detect AMI in ECGs with LBBB using artificial neural networks, the performance of the neural networks being compared with that of six sets of conventional ECG criteria and two experienced cardiologists.

Methods

Study population

This retrospective study was based on ECGs recorded at the emergency department of the University Hospital in Lund, Sweden from July 1990 to May 1997. Each ECG was classified as being AMI if the recorded ECG originated from a patient who was discharged from the coronary care unit with the diagnosis of AMI. If the ECG originated from a patient who was discharged with a diagnosis other than AMI, it was classified

as being a 'control ECG'. All ECGs with technical deficiencies and pacemaker ECGs were excluded from both groups.

During the study, the AMI diagnosis required at least two of the following three criteria to be met:

characteristic chest pain lasting >20 min,

elevated creatine kinase levels,

characteristic serial ECG changes.

Creatine kinase-B values greater than 0.23 µkat l^{-1} with a typical rise and fall were used as diagnostics for AMI. The ECG evidence including new Q waves in at least two adjacent leads and/or persistent T inversions in more than two adjacent leads after a newly developed ST elevation in those leads. A senior cardiologist at the department of cardiology confirmed each discharge diagnosis.

From the AMI and the control group, ECGs with LBBB were identified in a two step procedure. In the first step all ECGs with a QRS duration >120 ms were selected, this being based on the measurement program of the computerized electrocardiograph. In the second step a cardiologist visually analysed all ECGs selected in the first step and made the final selection according to the following criteria (Havelda et al., 1982):

QRS duration >120 ms,

QS or rS pattern in V1,

predominantly upright complexes with broad waves in the leads, aVL, I and V5 or V6.

After this procedure the final data set consisted of 518 ECGs with LBBB configuration, of which 120 were recorded on patients with AMI and 398 on control patients. The prevalence of LBBB was 6.8% in the AMI group and 3.6% in the control group.

The AMI group consisted of 74 ECGs recorded on males and 46 ECGs recorded on females. The mean age of the groups was 77.4 (± 9.1) years. The control group was composed of 202 ECGs recorded on males and 196 ECGs recorded on females. The mean age of this group was 75.7 (± 12.8) years.

Electrocardiography

The 12-lead ECGs were recorded by computerized electrocardiographs (Siemens-Elema AB, Solna, Sweden), with 11 measurements from each of the 12 leads being selected for further analysis: QRS duration, QRS area, Q, R and S amplitudes and six ST-T measurements (ST-J amplitude, ST slope, ST amplitude 2/8, ST amplitude 3/8, positive T amplitude and negative T amplitude). The ST amplitude 2/8 and ST amplitude 3/8 were obtained by dividing the interval between ST-J point and the end of the T wave into eight parts of equal duration. The amplitudes at the end of the second and the third intervals denoted ST amplitude 2/8 and ST amplitude 3/8. In total 132 measurements from each 12-lead ECG were used.

Because of the high degree of correlation between the measurements taken from the 12-lead ECGs, the data set comprising the 132 measurements for each case was reduced to a smaller set of more 'effective' variables by means of principal component analysis (Jollife, 1986). Prior to this analysis the measurements were grouped into the following eight sets of measurements namely: QRS durations, QRS areas, Q amplitudes, R amplitudes, S amplitudes, ST amplitudes, ST slopes and positive/negative T amplitudes. Each of these sets was then subjected to principal component analysis reduction, for example, the 12 ST slope measurements (one from each lead) were reduced to two variables. Using this technique the final data set was reduced to 30 variables.

Artificial neural networks

A general introduction to the subject of artificial neural networks can be found elsewhere (Cross et al., 1995). Neural networks with standard feed-forward, multilayer perceptron architecture were used in this study. The networks contained one input layer, one hidden layer and one output layer. The input layer comprised 30 nodes, one for each of the input variables, the hidden layer contained 12 nodes and the output layer consisted of one node. The latter encoded the output as to whether the patient suffered from AMI or not.

A Kullback–Liebler error function was implemented together with a Langevin extension (Rögnvaldsson, 1994) of the back-propagation updating rule. Langevin updating consists of adding a random Gaussian component to the weight updates, which has the effect of speeding up the minimization procedure.

To assess the generalization performance a test set is needed. A common procedure is to divide the full data set into one test set and one training set, using the training set to construct the neural networks and test its performance on the test set. To reduce a possible bias because of a particular test/training split, the full data set (518 ECGs) was randomly divided into three equally sized subsets (172/173/173). This division resulted in three unique test sets and their corresponding training sets. For each of the three training sets a neural network classifier was constructed and its performance was tested on the corresponding test set. The results presented in this paper are based on all three test sets, thus comprising the full data set. It is important to notice that each of the test sets was never part of the training procedure, which is described below and was repeated three times, one for each training set.

When training a neural network, particularly for small sized training sets, it is important to avoid over-training, which often decreases the generalization ability. For the neural networks used in this paper a weight elimination regularization term was employed (Hanson & Pratt, 1989). The amount of regularization is controlled by a regularization parameter. This was determined using a five-fold cross-validation scheme on the training set, where a range of regularization parameters were tested. The regularization parameter that corresponded to the smallest average validation error was selected and used for training a committee of 50 neural networks on the full training set. The output from the committee was calculated as the mean of the output from all 50 neural network members.

All calculations were undertaken using the JETNET 3·0 package (Peterson *et al.*, 1994).

Cardiologists

The performance of the neural networks was compared with that of two cardiologists, one, the head of the coronary care unit had 25 years of experience in reading ECGs and the other 10 years. The 518 ECGs were presented to the cardiologists in random order without any supporting information and each ECG was then classified independently by the cardiologists as AMI or not AMI.

ECG criteria

The performance of the neural networks was also compared with those of six sets of conventional rule-based criteria used for the detection of AMI in the presence of LBBB. Four of these criteria, listed below and denoted A–C (Sgarbossa *et al.*, 1996) and D (Hands *et al.*, 1988), have been evaluated in previous studies. In addition two further criteria, E and F were also used; Criterion E was defined as the combination of criteria A–C formed by means of the operation logical OR and criterion F the A–C combination formed by the operation logical AND. Consequently, criterion E was met if at least one of the three criteria A–C were fulfilled, whilst criterion F was met if all three of the criteria A–C were fulfilled. Thus the following six criteria were evaluated:

   A ST segment elevation >1 mm and concordant with QRS complexes in any lead.
   B ST segment depression >1 mm in V1, V2 or V3.
   C ST segment elevation >5 mm and discordant with QRS complexes in any lead.
   D Q waves in at least two of leads I, aVL, V5 or V6.
   E criteria A or B or C
   F criteria A and B and C

These criteria were evaluated using a computer program where the ST segment elevation was taken as the ST-J amplitude and concordant/discordant was defined as positive/negative QRS area.

Statistical methods

The sensitivity and specificity of the two cardiologists, the criteria A–F and the receiver operating characteristic (ROC) curve of the neural network were calculated and plotted. The technique used for comparing the neural network and cardiologists, and also for comparing the network and the criteria was performed as follows. The threshold applied to the network outputs was chosen so that the specificity for the neural network had the same value as the specificity for the cardiologist/criteria. Thereafter the corresponding network sensitivity was compared with that of the cardiologist/criteria. The significance of a difference in sensitivity was tested paying particular attention to the fact that the same ECGs were used, i.e. a McNemar type of statistic was used (Riffenburgh, 1999).

Results

The ROC curve of the neural network is plotted in Fig. 1 together with the results of the two cardiologists and the criteria A–F. The sensitivities and specificities with 95% confidence intervals of the criteria and the cardiologists are presented in Table 1. The sensitivity of the neural networks compared at the same levels of specificity as the criteria and cardiologist are presented in the same table.

These results show that the sensitivity of the neural network was 12% (P = 0·02) and 19% (P = 0·001) higher than that of the two cardiologists when compared at the same levels of specificity. Both cardiologists and the criteria C and D showed a specificity close to 80%, but the sensitivity of the criteria was much lower than those of the cardiologists. Criterion A (ST elevation concordant with QRS complexes) had a very high specificity as had criterion F, which was met when all three criteria A–C were fulfilled, but the corresponding sensitivities were very low. The criteria with highest sensitivity were B (ST depression in V1–V3) and E, which were fulfilled when at least one of the criteria A–C were met.

The neural network showed significantly higher sensitivity in comparison with criteria B–F when compared at the same levels of specificities. The sensitivity of the network was also higher than that of criterion A (27 vs. 22%) but this difference was not statistically significant.

Discussion

The results of this study show that it is possible to detect AMI in ECGs with LBBB using artificial neural networks. The performance of the networks was better than that of conventional rule-based criteria and even better than that of two experienced cardiologists. These results are in accordance with earlier studies
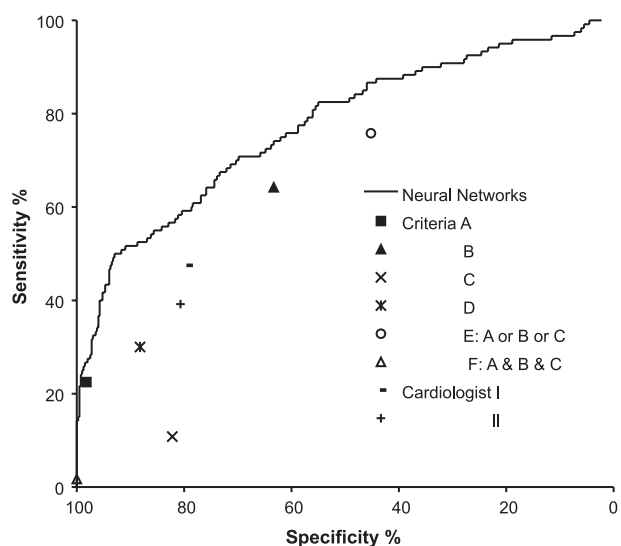

Figure 1 ROC curve for the neural networks diagnosing AMI in ECGs with LBBB. Sensitivities and specificities of the two cardiologists and the criteria are also indicated.

	Specificity	Sensitivity		
		Crit /cardiol	Neural network	P-value
Criteria				
A	98 (96–99)	22 (16–31)	27 (19–36)	0·25
B	63 (58–68)	64 (55–73)	74 (65–82)	0·02
C	82 (78–86)	11 (6–18)	57 (47–66)	<0·001
D	88 (85–91)	30 (22–39)	52 (43–62)	<0·001
E (A or B or C)	45 (40–50)	76 (67–83)	87 (79–92)	0·007
F (A and B and C)	100 (99–100)	2 (0–6)	14 (9–22)	<0·001
Cardiologists				
I	79 (75–83)	47 (38–57)	59 (50–68)	0·02
II	81 (76–84)	39 (31–49)	58 (49–67)	0·001

Table 1 Comparisons of neural network, conventional criteria and cardiologists performance. The values in parenthesis represent 95% confidence intervals.

where neural networks have shown high performance in the diagnosis of acute and healed myocardial infarction (Heden *et al.*, 1994, 1996, 1997). The performance of the networks in those studies was also better than that of rule-based criteria and experienced ECG readers.

The artificial neural networks used in this study were trained and tested on ECGs recorded at the emergency department on an unselected group of patients with AMI, the prevalence of LBBB in the population being 6·8%. This particular group has a higher LBBB prevalence than previous studies which used selected samples drawn from patients with myocardial infarction: Gusto 1 material (Sgarbossa *et al.*, 1996) and material from the multi-center investigation of the limitation of infarct size (MILIS) study (Hands *et al.*, 1988) where the prevalence was 131/26003 (0·5%) and 35/985 (3·5%), respectively. In the control population the prevalence of LBBB was 3·6%, this being in line with earlier epidemiological studies of the prevalence of LBBB which showed prevalence rates of 1·4% at the age of 67 and 5·7% at 80 years (Eriksson *et al.*, 1998). Because the results of this study is based on an unselected population of patients with LBBB we believe that the techniques developed could also be applied in other emergency departments with the same level of accuracy.

Today the use of reperfusion therapies, either as thrombolysis or acute percutaneous transluminal coronary angioplasty (PTCA), improves the prognosis (Muller & Topol, 1990; Kleiman *et al.*, 1994) and their efficiency is enhanced the earlier they are initiated. However thrombolysis administered to a patient with unstable angina or non-cardiac chest pain is potentially harmful. The ECG is a fast and easily available diagnostic tool, but the analysis is difficult in cases with LBBB. The appearance of a new LBBB in patients with chest pain is highly suggestive of AMI and new ischaemic ECG-changes in patients with previous ECGs possessing chronic LBBB are sometimes possible to identify by comparison. However, earlier ECGs are frequently not available and therefore this study focused on the interpretation of single ECGs by neural networks, cardiologists and criteria.

The objective for the complete training-test procedure employed in this paper was to estimate the true generalization performance that one can achieve with a neural network classifier. It is important to notice that a slightly different training procedure should be used when constructing a neural network classifier that can evaluate completely new ECGs. However, the expected performance on new ECGs should conform to the figures obtained in this study.

In conclusion, it has been demonstrated that artificial neural networks can be trained to detect AMI in ECGs with concomitant LBBB. In addition it has also been shown that the networks' performance is superior to both conventional criteria currently in use, as well as experienced cardiologists.

Acknowledgements

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