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

Sven-Erik Olsson[1], Hans Öhlin[1], Mattias Ohlsson[2], Lars Edenbrandt[3]

[1]Departments of Cardiology, [2]Theoretical Physics, and [3]Clinical Physiology, Lund University, Lund, Sweden

Address for correspondence:

Sven-Erik Olsson

Department of Cardiology

University Hospital

SE-221 85 Lund

Sweden

Telephone	+46 46 17 35 18
Fax	+46 46 15 78 57
E-mail	sven-erik.olsson@kard.lu.se

Abstract

Introduction: The prognosis of acute myocardial infarction (AMI) improves by early revascularisation. The presence of left bundle branch block (LBBB) in the electrocardiogram (ECG) makes it difficult to recognize an AMI. Different ECG criteria for the diagnosis of AMI in the presence of LBBB have proved to be of limited value. On the other hand artificial neural networks have successfully been applied to diagnose AMI from the ECG. The purpose of this study was to detect AMI in ECGs with LBBB using an artificial neural network.

Methods: A total of 518 ECGs, recorded at the emergency department, with a QRS duration >120 ms and an LBBB configuration were selected from the clinical ECG database. Of these 120 ECGs were recorded on patients with AMI. The remaining 398 ECGs were used as a control group. Artificial neural networks of feed-forward type was trained to classify the ECG as AMI or not AMI. After the training process the performance of the neural networks was evaluated in separate test sets and compared to that of six sets of conventional ECG criteria and two experienced cardiologists.

Result: The neural network showed higher sensitivities than both cardiologists and the criteria 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 two cardiologists.

Discussion: Artificial neural networks can be trained to detect AMI in ECGs with concomitant LBBB with high accuracy. This type of networks may be useful as decision support even for the experienced cardiologists.

Introduction

The prognosis of acute myocardial infarction (AMI) improves by early revascularisation (1-2). Early diagnosis of AMI is therefore of vital importance and the 12-lead electrocardiogram (ECG) is still the most readily available and best diagnostic investigation. The presence of left bundle branch block (LBBB) makes the electrocardiografic manifestations of acute myocardial transmural ischemia difficult to detect. This diagnostic problem is not uncommon. In unselected populations of patients with myocardial infarction the prevalence of LBBB has shown to be 5-10 % (3).

According to the recommendation of the ACC/AHA (4), patients presenting with symptoms suggestive of AMI and concomitant LBBB should be considered for revascularisation. Using this approach there is a risk that patients without AMI are treated with revascularisation. The acute revascularisation involves procedures of high risc of bleeding or of high costs. The opposite approach, not to treat patients with LBBB, would exclude these patients with AMI from the benefits of a revascularisation procedure. It is therefore of interest to find more accurate methods for the early diagnosis of AMI in patients with LBBB.

Artificial neural networks have been applied to different aspects of automated interpretation of ECGs, for example for the diagnosis of healed myocardial infarction (5-6) and AMI (7). In these studies the neural networks showed a significantly better performance than 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 was compared to that of six sets of conventional ECG criteria and to that of two experienced cardiologists.

Methods

Study Population

This study was based on all ECGs recorded at the emergency department of the University Hospital in Lund, Sweden from July 1990 to May 1997. During this period 1,846 ECGs were recorded on patients who were admitted to the coronary care unit or a medical ward after the recording, and were discharged with the diagnosis AMI. During the same time period 24,825 ECGs were recorded on patients without verified AMI. ECGs with technical deficiencies and pacemaker ECGs were excluded. It could be a disadvantage in the neural network training procedure to have many more control ECGs than AMI ECGs. Therefore the number of control ECGs was reduced to 11,086 by including only the first ECG recorded on each patient and including only ECGs recorded on patients older than 40 years of age.

During the study period, the policy of the diagnosis of AMI was as follows. At least two of the following three criteria must have been fulfilled: characteristic chest pain lasting >20 minutes, elevated creatine kinase levels, and characteristic serial ECG changes. Creatine kinase-B values >0.23 μkat/L with a typical rise and fall were used as diagnostics for AMI. ECG evidence of AMI included 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.

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 analysis was based on the measurement program of the computerized electrocardiograph. In the second step a cardiologist visually analyzed all ECGs selected in the first step and made the final selection according to the following criteria

(i) QRS duration >120ms, (ii) QS or rS pattern in V1, (iii) predominantly upright complexes with broad waves in the leads aVL, I, and V5 or V6 (8)

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 was 77.4 (±9.1) years. There were 202 ECGs recorded on males and 196 ECGs recorded on females in the control group. The mean age was 75.7 (±12.8) years.

Electrocardiography

The 12-lead ECGs were recorded by the use of computerized electrocardiographs (Siemens-Elema AB, Solna, Sweden). The following 11 measurements, from each of the 12 leads were 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 were denoted ST amplitude 2/8 and ST amplitude 3/8. In total 132 measurements from each 12-lead ECG were used.

There is a high degree of correlation between the measurements from the 12-lead ECGs. The data set comprising 132 measurements for each case was reduced to a smaller set of more "effective" variables. The reduction was accomplished using principal component analysis (9). Prior to this analysis the measurements were grouped into the following eight sets of measurements namely: QRS duration, QRS area, Q amplitudes, R amplitudes, S amplitudes, ST amplitudes, ST slope, and positive/negative T amplitudes. Each of these sets were then subject to a principal component analysis reduction. For example, the 12 ST slope measurements (one from each lead) were reduced to 2 variables. The final data set was reduced to 30 variables.

Artificial Neural Networks

Feed-forward artificial neural networks with a standard multilayer perceptron architecture were used. A general introduction to the subject can be found elsewhere (10). The neural networks consisted of one input layer, one hidden layer and one output layer. There were 30 nodes in the input layer, one for each of the input variables. The hidden layer contained 12 nodes. The output layer consisted of one node that encoded whether the patient suffered from AMI or not.

A Kullback-Liebler error function was used together with a Langevin extension (11) 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. In order to assess the generalization performance the full data set was divided into 3 equally sized parts. Each of these parts was used as test set and the remaining two parts was used as a training set in a 3-fold cross validation scheme. In order to avoid over-training a weight elimination regularization term was used (12). The regularization parameter α was set using an additional 5-fold cross-validation scheme on the training set, i.e. an average validation error was calculated as the mean of the 5 individual validation errors and the α that corresponded to the smallest average validation error was selected as the optimal α. Finally, a committee of 50 networks was trained on the full training set using the obtained regularization parameter α. All calculations were done using the JETNET 3.0 package (13).

The output values for test ECGs were in the range from 0 to 1. A threshold in this interval was used above which all values were regarded as consistent with AMI. For each threshold a sensitivity/specificity pair was calculated. By varying this threshold a receiver operating characteristic (ROC) curve was obtained.

Cardiologists

The performance of the neural networks was compared to that of the two cardiologists. One was the head of the coronary care unit and he had 25 years of experience in ECG reading. The other cardiologist had 10 years of experience in ECG reading. The 518 ECGs were presented to the cardiologists in random order without any clinical data or the results of neural networks. Each ECG was classified independently by the two cardiologists as AMI or not.

ECG Criteria

The performance of the neural networks was also compared to those of six sets of conventional rule-based criteria for the detection of AMI in the presence of LBBB. The criteria denoted A-C (14) and D (15) have been evaluated i previous studies. In addition the criteria A-C were combined in the criteria denoted E and F. Criteria E is fulfilled if at least one of the three criteria A-C are fulfilled. Criteria F is fulfilled only if all three of the criteria A-C are fulfilled. The following six criteria were evaluated:

A. ST segment elevation > 1mm and concordant with QRS complexes in any lead

B. ST segment depression > 1mm in V1, V2 or V3.

C. ST segment elevation > 5mm 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

Statistical Methods

Sensitivity and specificity for the two cardiologists and the criteria A-F were calculated and plotted together with the ROC curve of the neural network. The comparisons between the neural network and cardiologists, and between the network and the criteria were performed as follows. The threshold applied to the network outputs was chosen so that the specificity for the neural network was the same as the specificity for the cardiologist/criteria. Thereafter the corresponding sensitivity of the network was compared to that of the cardiologist/criteria. The significance of a difference in sensitivity was tested paying attention to the fact that the same ECGs were used, i.e. a McNemar type of statistics was used.

Results

The ROC curve of the neural network and the results of the two cardiologists and the criteria A-F are shown in Figure 1. The sensitivities and specificities of the cardiologists and the criteria are presented in Table 1. The sensitivity of the neural network compared at the same levels of specificity as the cardiologist/criteria are presented in the same table.

The sensitivity of the neural network was 12% (p=0.02) and 19% (p=0.001) higher than that of the two cardiologists compared at the same levels of specificity. Both cardiologists and the criteria C and D showed a specificity close to 80%. The sensitivity of criteria C was only 11%, but criteria D showed a sensitivity nearly as high as the best cardiologist.

Criteria A (ST elevation concordant with QRS complexes) had a very high specificity as had criteria F, which were fulfilled if all three criteria A-C are fulfilled. The corresponding sensitivities were very low. The criteria with highest sensitivity were criteria B (ST depression in V1-V3) and criteria E, which were fulfilled if at least one of the criteria A-C were fulfilled.

The neural network showed sigificantly higher sensitivity compared to criteria B-F compared at the same levels of specificity. The sensitivity of the network was also higher than that of criteria 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 where neural networks have shown high performance concerning the diagnosis of acute and healed myocardial infarction (5-7). 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 in this study were trained and tested using ECGs recorded at the emergency department on an unselected group of patients with AMI. The prevalence of LBBB in the AMI population was 6.8 %. This number is in line with other studies of unselected AMI material (3).

In the control population the prevalence of LBBB was 3.6%. This number is in line with earlier epidemiologic studies of the prevalence of LBBB of 1.4 % at the age of 67 years and prevalence of 5.7 % at the age of 80 years (3).

Acute chest pain in a patient with efforts an diagnostic challenge whether the patient suffers from AMI or not. Common algorithms of ECG analysis do not apply in patients with LBBB. Today use of reperfusion therapies either as thrombolysis or acute PTCA improves the prognosis (1-2). The effect of reperfusion is higher the earlier it is initiated. On the other side thombolysis administerd to a patient with unstable angina or non-cardiac chest pain is potentially harmful. The ECG is a fast and easily available diagnostic tool. Appearance of a new bundle branch block are highly suggestive of AMI. Ischemic changes compared to earlier ECG in patients with chronic bundle branch block are often possibly to identify. Unfortunately it is not unusual there are no earlier ECG to compare with. In this study we have trained and evaluated an artificial neural network by using unsorted ECG from patients with AMI registred at an universityhospital. Emergency department. The neural network showed significantly better performance than (criteria B-F) conventional criteria or the two cardiologist. Criteria A has low sensitivity and is not a criterion which in a clinical setting can be used as the only criterion.

Study limitations

The control group consists of patients admitted to the emergency department. In this group sub-acute non diagnosed AMI can not be ruled out but may not reflect the performance of the neural networks in a negative way.

Conclusion

Artificial neural networks can be trained to detect AMI in ECGs with concomitant LBBB with high accuracy. The results of this study suggest the artificial neural networks in the future may become a tool for decision support in patients with symptoms suggestive of AMI and concomitant LBBB. This type of networks may be useful as decision support even for the experienced cardiologists.

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Table 1:

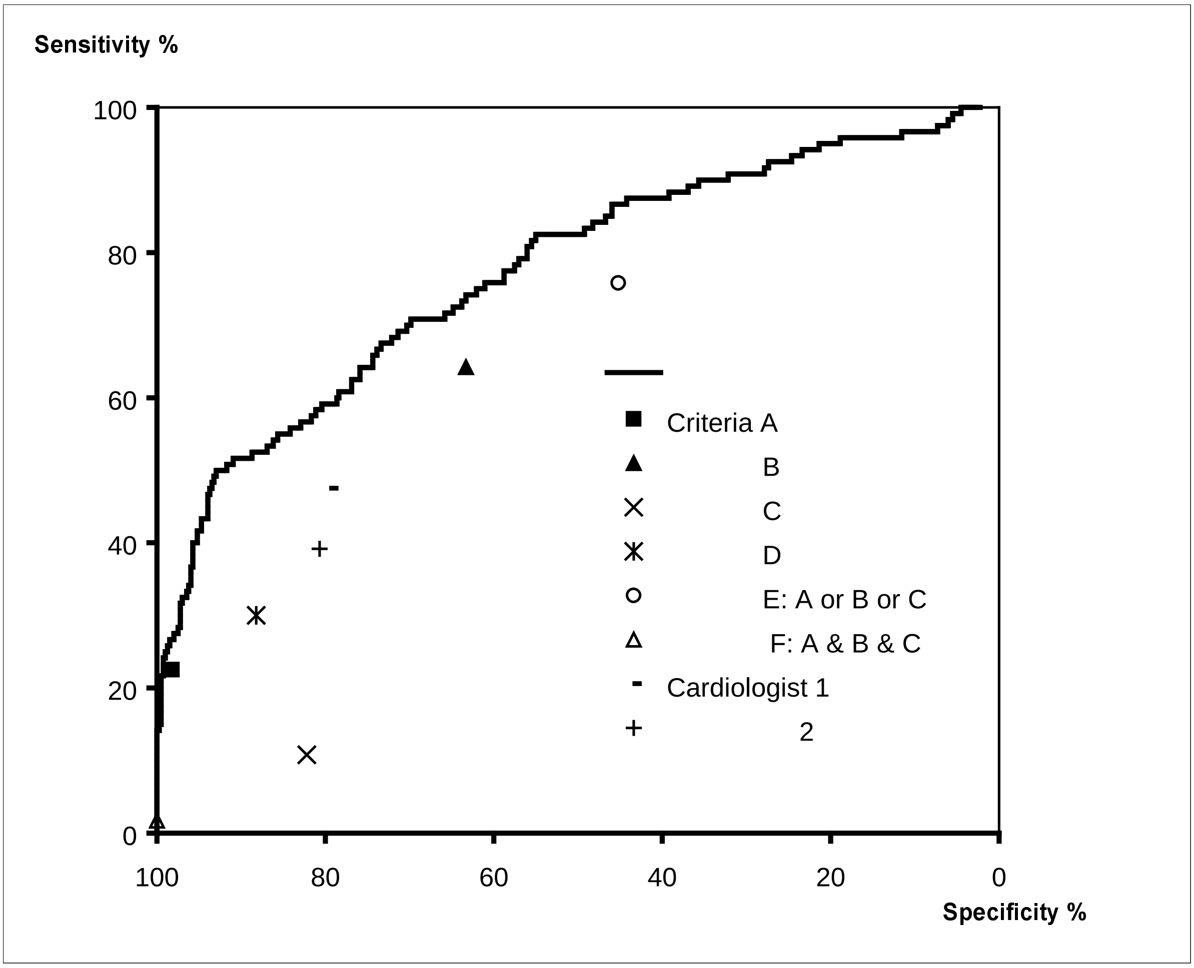
Comparisons of neural network, conventional criteria, and cardiologists performance.

	Specificity	Sensitivity		
		Crit/Cardiol	Neural Network	p-value
Criteria				
A	98	22	27	0.25
B	63	64	74	0.02
C	82	11	57	< 0.001
D	88	30	52	< 0.001
E (A or B or C)	45	76	87	0.007
F (A and B and C)	100	2	14	< 0.001
Cardiologists				
I	79	47	59	0.02
II	81	39	58	0.001

Figure legend

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.



Sensitivity %
100
80
60
40
20
0
100
80
60
40
20
0
Specificity %
Criteria A
B
C
D
E: A or B or C
F: A & B & C
Cardiologist 1
2